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EDITORIAL NOTES

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In the web publication of JBET, the editors have chosen to present JBET in a single column (margin-to-margin) instead of the traditional two-column presentation of an academic journal. We have done this to enhance readability in the web presentation.

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ABSTRACT

This paper pays a revisit to some of the elementary properties of budget sets, demand correspondences of the prevalent consumer theory by clearly distinguishing three binary relations, $\leqq$ defined on the Euclidean space $\mathbb{R}^{\ell}$, $\precsim_i$ on consumer i's set X_i of all possible consumptions, $\leq_i$ on real numbers. It explores the relationship between an individual's consumption preferences and his specific order $\leq_i$ of real numbers; and shows that these visited properties are not generally true unless $\leq_i$ is equal to the conventional order $\leq$ of real numbers and/or $\precsim_i$ is complete, reflexive and transitive on X_i. Additionally, this paper constructs four counterexamples to demonstrate that (i) when $\leq_i \neq \leq$, the continuity of the budget set is in doubt; (ii) generally, an individual consumer's demand correspondence is not homogeneous of degree zero; (iii) the preference relation $\precsim_i$ is generally not additively conservative or positively multiplicative; and (iv) not every preference relation $\precsim_i$ is asymptotically preserving. In the final section, this paper also suggests topics for future research.

INTRODUCTION

Each consumer, be it an individual or a business firm, undergoes lifecycle stages, such as birth, growth, maturation and death. To maintain survival, every individual and business must first satisfy basic physiological or functional business needs before consuming any luxury products, goods, or services. These needs are generally multidimensional in nature. For example, in order to house a physical or virtual existence, a shelter or an office domain is needed first. In order to satisfy physiological needs or to maintain operational demands, various nutritional intakes or business inputs are required. When two consumption choices from different dimensions are presented, the consumer cannot truly tell which alternative is preferred to the other. For example, for an individual person, tickets to different world series games and soft drink choices represent examples of consumption alternatives from two different dimensions; for a business firm, personnel needed for maintaining regular operational routines and talent required for innovative R&D purposes are also examples of consumption choices from different dimensions. In either of these two scenarios, the consumption alternatives cannot be directly compared by using the individual consumer's or the business firm's preferences. Speaking differently, only when two consumption alternatives come from the same dimension, a consumer *might* be able to make a pick based on what he prefers. This recognition of incompleteness is different from that as noticed before from the angle of bounded rationality and consumers' indecisiveness (Aumann, 1962; Bewley, 1986; Mandler, 1999; Ok, 2002).

Because of the existence of such multidimensionality with consumption choices, one can readily see that a consumer's set of all possible consumptions cannot be completely ordered by his/its preferences. Hence, to make the relevant economic theory, such as the consumer theory, practically useful in real life, we cannot continue to assume that consumer preferences can compare any two consumption alternatives, as conventionally done as in widely used textbooks and lecture notes (Levin & Milgrom, 2004; Mas-Collel et al., 1995). The existence and maintenance of this convention, to a large extent, are due to the desire for the community of economists to develop a theory that is mathematically beautiful and satisfactory, for more details about this end, see von Neumann and Morgenstern (1944, p. 29) and Paul Krugman's comment (New York Times, 2009-09-02). Therefore, the following question naturally arises at this junction. Can we reestablish the key conclusions of the prevalent consumer theory regarding a consumer's budget set and demand correspondence without assuming the completeness of consumption preferences?

As expected, this paper demonstrates that when the assumed completeness is replaced by incompleteness, all related conclusions regarding a consumer's budget set and demand correspondence mostly take their correspondingly different forms or only hold true conditionally. And, because the incompleteness assumption is much closer to real life, one can expect the consequent conclusions to be more useful than the conventional ones in terms of their explanation abilities. Compared to what we attempt to do here, there are also parallel efforts in the literature. For example, when it is recognized that preference relations generally only satisfy reflexivity without completeness and transitivity, Ok (2002), Bosi and Herden (2012) and Nishimura and Ok (2016) consider the problem of how to represent an incomplete preference relation by means of a collection of real-number valued functions. This end is parallel to the classical conclusion that a complete preference relation can be possibly represented by a real-number valued utility function.

The rest of this paper is organized as follows. After outlining the basic model and relevant terminologies needed for the rest of this presentation, we turn our attention to the continuity of a consumer's budget set, the demand correspondence of an individual, and some properties of the total demand correspondence. With the success of establishing the relationship between consumption preferences and the order of real numbers, the paper is concluded with several suggestions for future research topics.

PREPARATIONS

This section consists of two parts. The first part details the basic setup for the reasoning of the rest of the paper regarding how a consumption is theoretically constructed and points out the differences among three order relations. The second part examines the concept and elementary properties of modular functions needed for us to construct counterexamples.

Possible Consumptions of a Consumer

A consumer can be an individual, a firm or an organization that decides what a package of different commodities to consume now for the current time and the future, as is in the literature (Debreu, 1959; Levin & Milgrom, 2004; Mas-Collel et al., 1995). Such a package is referred to as the consumer's consumption plan (or consumption). The consumer determines how much each of the chosen commodities he will consume and offer within a set of constraints. As examples, the constraints consist of those commodities necessary for survival, those possible within budget, etc.

Consider such a market that contains m consumers, for some $m \in \mathbb{N}$ (= the set of all natural numbers). For consumer i (= 1, 2, …, m), the amounts of his commodity inputs that are to be consumed are represented as positive numbers; and those of his commodity outputs, offer to the market, are written as negative numbers. Without loss of generality, assume that all commodities, totaling to ℓ different kinds, are ordered by their names as $h = 1, 2, \ldots, \ell$. By following this convention (e.g., Pancs, 2018), assume that the quantity of each commodity in a consumption plan is a real number.

Without explicitly mentioning, assumed in this model setup include (i) perfect information, (ii) each consumer is a price taker; and (iii) prices are linear without quantity discount. In particular, (i) means that each consumer knows exactly how much each commodity will be consumed.

Let $X_i \subseteq \mathbb{R}^\ell$, where $\mathbb{R}$ is the set of all real numbers (in the rest of this paper, $\mathbb{R}_+$ stands for the set of all positive real numbers), be the set of all consumptions possible for consumer i. It is referred to as the consumer's consumption set or demand. For each $x_i \in X_i$, the typical inputs consist of dated and location-specific products, goods and services, while the outputs are various kinds of dated and location-specific labors. In other words, products, goods, services, and labors, delivered at different times and/or different locations, are treated as different commodities.

If commodity h is contained in an $x_i \in X_i$ with a positive quantity, then consumer i inputs h so that this quantity must have a lower bound, such as zero. If h is contained in $x_i \in X_i$ with a negative quantity, then h is an output commodity of consumer i so that this quantity must also have a lower bound. It is because the consumer can only produce a limited amount of labor output at any time moment. Based on this analysis, we introduce the following axiom:

Axiom 1 (Lower Boundedness): For each consumer $i\ (= 1,2, \ldots, m)$, his consumption set X_i has a lower bound for the order relation $\leqq$ defined on $\mathbb{R}^\ell$, defined as follows: For any $x^1, x^2 \in \mathbb{R}^\ell$,

$$x^1 \leqq x^2 \text{ if and only if } x_h^1 \leq x_h^2, \text{for } h = 1,2, \ldots, \ell. \quad (1)$$

For two consumptions $x_i^1, x_i^2 \in X_i$, if consumer i prefers x_i^1 at least as much as to x_i^2, then we write $x_i^1 \gtrsim_i x_i^2$ or, equivalently, $x_i^2 \lesssim_i x_i^1$. That means that there is a preference relation $\lesssim_i$ on X_i such that the axiom holds true.

Axiom 2 (Comparability). If $x_i^1, x_i^2 \in X_i$ are comparable in terms of consumer i's preference, as determined by his system of values and beliefs, then one and only one of the following alternatives holds true:

(i) x_i^1 is preferred to x_i^2, written as $x_i^1 \gtrsim_i x_i^2$;
(ii) x_i^1 is indifferent to x_i^2, written $x_i^1 \sim_i x_i^2$; and
(iii) x_i^2 is preferred to x_i^1, written $x_i^1 \lesssim_i x_i^2$.

The concept of individuals' systems of values and beliefs are first employed in the study of abstract economic studies by Forrest, Wu et al. (2022). A similar, but different concept, known as tastes (Stigler & Becker, 1977), was used in similar setting. In particular, tastes represent a reason for people to act in different ways. Against the conventional view of tastes, which are seen as inscrutable and often capricious, Stigler and Becker (p. 76) believe that "tastes neither change capriciously nor differ importantly between people." In comparison, an individual's system of values and beliefs also dictate how an individual would act in specific ways, and do not change easily (Lin & Forrest, 2012), similar to Stigler and Becker's interpretation of tastes. But, from one person to another, their underlying systems of values and beliefs can change drastically, leading to, for example, different orderings of real numbers and different priorities of matters. For example, driven by their specific systems of values and beliefs, some people take pleasure in their acts of harming others, while some other people would prefer to treating each other with respect. For the former people, they most likely see \$3 million as a greater amount than \$3 K, while the latter would very possibly see \$3 K as an amount greater than \$3 million if these millions are the outcome of successfully robbing a bank. In other words, differences in systems of values and beliefs are more than differences in relative costs, which are one of the most commonly examined variables by neoclassical economists. Because differences in values and beliefs can easily lead to different orderings of real numbers, comparing costs can be done differently from one individual to another.

Assume that $\leq_i$ (respectively, $<_i$, $>_i$, $\geq_i$, $=_i$) represents consumer i's order of real numbers. There are then three order relations involved here: (i) $\leqq$ (respectively, $<$, $>$, $\geqq$, $=$) defined in $\mathbb{R}^\ell$, as given in equation (1), (ii) $\lesssim_i$ (respectively, $\prec_i$, $\succ_i$, $\gtrsim_i$, $=_i$) defined on X_i, and (iii) $\leq_i$ (defined on $\mathbb{R}$). One needs to note that different from both $\leqq$ and $\leq_i$, consumer i's consumption preferences $\lesssim_i$ in real life are generally influenceable by peers and frequently altered temporarily by peer pressures, especially for emerging adults (Hu et al., 2021; Li et al., 2023; Mani et al., 2013). Because time does not play a role in this paper, the preference relation $\lesssim_i$ becomes fixed and not influenceable by peers.

The binary relation $\lesssim_i$ is said to be a preorder, if it satisfies (i) reflexivity: for any $x_i \in X_i$, $x_i \lesssim_i x_i$; and (ii) transitivity: for any $x_i^1, x_i^2, x_i^3 \in X_i$, $x_i^1 \lesssim_i x_i^2$ and $x_i^2 \lesssim_i x_i^3$ imply $x_i^1 \lesssim_i x_i^3$. It is said to be complete, if each pair $x_i^1, x_i^2 \in X_i$ can be compared by $\lesssim_i$. To make our conclusions closer to real life situations, the preference relation $\lesssim_i$ considered in this paper is not generally assumed to be a complete preorder unless it is specifically mentioned so.

Without loss of generality, we assume that $\leq_i$ is reflexive, transitive and antisymmetric (for any $a, b, c \in \mathbb{R}$, $a \leq_i b$ and $b \leq_i c$ imply $a \leq_i c$). Please note that this assumption does not mean that $\lesssim_i$ is rational or that $\lesssim_i$ is reflexive, transitive and complete (Mas-Collel et al., 1995).

The Modular Function

When looking at a real-life economic process, one often sees seasonalities or periodicities. For example, when looking at the time variable underneath an economic process, the economic activities that are carried out in the process are periodically checked, such as annually or quarterly. If the time length of the basic period is denoted by a positive real number r, then the modular function $\mathrm{mod}(r)$ appears. With this understanding, the time line (or the real number line) becomes a circle of circumference r on which a point travels one loop after another starting at the origin without end in sight, Figure 1.

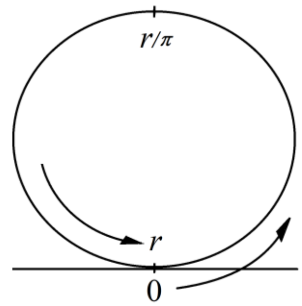

Figure 1. A model of the mod(r) function

To make the concept of modular functions in the previous paragraph clearer, one can use the semester system of a school as an example. Assume that the student evaluation of every course contains a question on student learning and the effectiveness of professor's teaching. Due to differences in the value and belief systems of individual professors, each professor generally employs his unique approach to maximize students' learning. To this end, it has been well known in real life that the outcomes of individual professors' maximum students' learning are most likely inconsistent with each other. In other words, although each chosen optimum approach comes out of the same objective function, professors with different systems of values and beliefs generally produce different optimal outcomes. In this case, the length of one school semester is the modular r value, over which professors seek for their individually unique ways to deliver their effective teaching so that students' learning can be maximed.

Conventionally, the mod(r) function is defined for natural number $r > 1$ (Burton, 2012). For a different purpose, Forrest, Hafezalkotob et al. (2021) generalized it to the case of any positive real number r. Specifically, for a chosen positive number $r \in \mathbb{R}$, a linear order relation $\leq_{mod(r)}$ on $\mathbb{R}$ can be defined as follows: For real numbers x and $y \in \mathbb{R}$,

$$x <_{mod(r)} y \text{ if and only if } x\ mod(r) < y\ mod(r),$$

where the ordering $<$ is the conventional one defined on $\mathbb{R}$, $x\ mod(r)$ is the remainder of $x \div r$ and $y\ mod(r)$ the remainder of $y \div r$, such that $0 \leq x\ mod(r) < r$ and $0 \leq y\ mod(r) < r$. Intuitively speaking, the application of the modular operation makes real numbers wrap around a circle of circumference r (Figure 1), known as modulus. When $b = x\ mod(r) > 0$, b stands for the point on the circle that is of an arc distance b in the counterclockwise direction from point 0; and when $b = x\ mod(r) < 0$, b stands for the point on the circle that is of an arc distance b in the clockwise direction from point 0. When r, x, and y consider here are limited to the set $\mathbb{Z} = \{\dots, -3, -2, -1, 0, +1, +2, +3, \dots\}$ of integers, the afore-defined order relation $\leq_{mod(r)}$ degenerates into the one widely studied in number theory (Burton, 2012).

MAIN CONCLUSIONS

This section is made up of four relatively independent subsections. In particular, the first subsection examines the continuity of a consumer's budget set, while a counterexample is constructed to show that without assuming consumer-specific order of real numbers is the same as the conventional one, a consumer's budget set cannot be shown to be continuous with the argument given here. The second subsection establishes four propositions regarding a consumer's demand correspondence. Expanding the scope of attention, the third subsection studies the total demand correspondence of all consumers. And the fourth subsection scrutinizes the relationship between preferences and orders of real numbers, while two counterexamples are constructed to demonstrate the necessity for the preference relation to satisfy the conditions of additive conservation and positive multiplicativity.

The Continuity of a Consumer's Budget Function

For consumer i, assume that he has accumulated a certain amount of wealth, denoted as a real number w_i. So, he chooses his consumption $x_i \in X_i$ subject to the constraint $p \cdot x_i \leq_i w_i$, for any given price system $p \in \mathbb{R}^{\ell}_{+}$ of commodities, where $p = (p_1, p_2, \dots, p_\ell)$ stands for the price vector of the commodities $h = 1,2, \dots, \ell$. As noted above, consumer i's order $\leq_i$ of real numbers is defined specifically by consumer i's system of values and beliefs. In terms of the literature, the consumer-specific order $\leq_i$ of real numbers has been assumed to be the same as the conventional one $\leq$ (Levin & Milgrom, 2004; Mas-Collel et al., 1995). Evidently, this commonly adopted order $\leq$ of real numbers reflects a certain category of systems of values and beliefs. However, there are such value-belief systems that dictate the ordering of real numbers differently. For example, corresponding to the concept of corporate social responsibilities (Liu et al., 2018; Poist, 1989), consumer i pledges to give back to the society by donating a portion of his wealth to his favorite charity organizations by employing the following scheme: as soon as the accumulation of his wealth reaches the level of, say, 30 units, he will donate away that entire 30 units of wealth. In other words, consumer i's consumption $x_i \in X_i$ is subject to the constraint $p \cdot x_i \leq w_i \, mod(30)$.

Because there are m consumers, the wealth vector $w = (w_1, w_2, \ldots, w_m) \in \mathbb{R}^\ell$ expresses the wealth distribution of the population of concern. The vector $(p, w) \in \mathbb{R}^{\ell+m}$ is referred to as the price-wealth pair (Debreu, 1959) of the population. Define the set of feasible price-wealth pairs of consumer i, for each $i = 1,2, \ldots, m$,

$$S_i = \{(p, w) \in \mathbb{R}^{\ell+m} : \exists x_i \in X_i \text{ such that } p \cdot x_i \leq_i w_i\},$$

and a set-valued budget function $\gamma_i: S_i \to X_i$: for any $(p, w) \in S_i$,

$$\gamma_i(p, w) = \{x_i \in X_i : p \cdot x_i \leq_i w_i\}, \tag{2}$$

where $\gamma_i(p, w)$ is referred to as the budget set of consumer i (Levin & Milgrom, 2004), when the price system is p and the wealth level is w.

A set-valued function $f: A \to B$, for A and $B \subseteq \mathbb{R}^\ell$, is said to be continuous at a point $a^0 \in A$ (Kuratowski & Mostowski, 1976), if f satisfies both

- (Upper semicontinuity at a^0) For any $\{a^q\}_{q=1}^\infty \subseteq A$ such that $a^q \to a^0 \in A$, if $b^q \to b^0 \in B$, for any $\{b^q\}_{q=1}^\infty \subseteq B$ with $b^q \in f(a^q)$, then $b^0 \in f(a^0)$; and
- (Lower semicontinuity at a^0) If $a^q \to a^0$ and $b^0 \in f(a^0)$, then there is $\{b^q\}_{q=1}^\infty \subseteq B$ with $b^q \in f(a^q)$ such that $b^q \to b^0$.

Proposition 1. Assume that each infinity can be actually (not potentially) achieved and that $\leq_i$ is the same as $\leq$. If a price-wealth pair $(p^0, w^0) \in S_i$ satisfies $w_i^0 \neq \min_{x_i \in X_i} p^0 \cdot x_i$, then γ_i is continuous at (p^0, w^0).

Proof. First, we show the upper semicontinuity. Assume that $\{(p^q, w^q)\}_{q=1}^\infty \subseteq S_i$ is a convergent sequence of price-wealth pairs such that $(p^q, w^q) \to (p^0, w^0) \in S_i$. Then,

$$\gamma_i(p^q, w^q) = \{x_i \in X_i : p^q \cdot x_i \leq w_i^q\}, q = 0,1,2, \ldots$$

For any convergent sequence $\{x^q\}_{q=1}^\infty$, $x_i^q \in \gamma_i(p^q, w^q)$, $q = 1,2, \ldots$, if $x_i^q \to x_i^0 \in X_i$, as $q \to \infty$, we need to show $x_i^0 \in \gamma_i(p^0, w^0)$. This end follows from the facts that $x_i^q \in X_i$ satisfies

$$p^q \cdot x_i^q \leq w_i^q \tag{3}$$

and that in Euclidean space $\mathbb{R}^{\ell+m}$, $(p^q, w^q) \to (p^0, w^0)$ is equivalent to $p^q \to p^0$ and $w^q \to w^0$. Hence, equation (3) implies that as $q \to \infty$, we have $p^0 \cdot x_i^0 \leq w_i^0$. That is, $x_i^0 \in \gamma_i(p^0, w^0)$.

Second, we show the lower semicontinuity. Assume that $\{(p^q, w^q)\}_{q=1}^\infty \subseteq S_i$ is a convergent sequence of price-wealth pairs such that $(p^q, w^q) \to (p^0, w^0) \in S_i$, and that $x_i^0 \in \gamma_i(p^0, w^0)$ so that $p^0 \cdot x_i^0 \leq w_i^0$. To conclude the rest of the argument, it needs to show the existence of an infinite sequence $\{x_i^q\}_{q=1}^\infty \subseteq X_i$ such that $p^q \cdot x_i^q \leq w_i^q$, for $q = 1,2, \ldots$, and $x_i^q \to x_i^0$, as $q \to \infty$. This is where the assumption that each infinity can be actually (not potentially) achieved comes into play. In particular, Lin (2008) documents that potential infinities and actual infinities are fundamentally different concepts; and they can lead to and have indeed led to completely inconsistent outcomes (Forrest, 2013), while the existence of the desired sequence $\{x_i^q\}_{q=1}^\infty \subseteq X_i$ mistakenly treated potential infinities as actual ones.

To understand the previous paragraph, let us briefly examine the concept of infinities. It involves two different types of infinities with one known as actual infinities and the other potential infinities (Lin, 2008). Specifically, a potential infinity represents a forever ongoing and never-ending process or procedure; and every actual infinity characterizes a process that actually ends or had ended. To see how this concept of infinities applied to our current situation, let us construct the desired sequence in two different cases: (i) $p^0 \cdot x_i^0 < w_i^0$; and (ii) $p^0 \cdot x_i^0 = w_i^0$.

For case (i), because $(p^q, w^q) \to (p^0, w^0)$, there is a subsequence $\{(p^q, w^q)\}_{q=q^*}^{\infty}$, for some large integer q^*, such that $p^q \cdot x_i^0 < w_i^q$, for $q = q^*, q^* + 1, q^* + 2, \ldots$ Now, each term x_i^q of the desired sequence $\{x_i^q\}_{q=1}^{\infty} \subseteq X_i$ can be constructed as follows:

$$x_i^q = \begin{cases} \text{an element in } \gamma_i(p^q, w^q), & \text{if } q \leq q^* \\ x_i^0, & \text{if } q > q^* \end{cases}$$

That is, for each chosen q, the term x_i^q is defined, representing a potential process, while the existence of the entire sequence $\{x_i^q\}_{q=1}^{\infty}$ stands for an actual infinity, where a forever ongoing process is assumed to be finished. That is, potential and actual infinities are seen as the same.

For case (ii). where $p^0 \cdot x_i^0 = w_i^0$, the assumption $w_i^0 \neq \min_{x_i \in X_i} p^0 \cdot x_i$ implies that there is $z_i \in X_i$ such that $p^0 \cdot z_i < w_i^0$. So, the assumed limit $(p^q, w^q) \to (p^0, w^0)$ implies that there is an integer q^*, such that for $q = q^*, q^* + 1, q^* + 2, \ldots$,

$$p^q \cdot z_i < w_i^q \text{ and } p^q \cdot z_i < p^q \cdot x_i^0. \tag{4}$$

For each q (=1, 2, …), let us respectively consider the following hyperplane determined by (p^q, w^q) and the line that passes through z_i and x_i^0:

$$p^q \cdot x_i = w_i^q \text{ and } x_i = x_i^0 + t(z_i - x_i^0),$$

for $x_i \in \mathbb{R}^\ell$ and $t \in \mathbb{R}$. It can be seen that the intersection a_i^q of this hyperplane and the line is determined by $a_i^q = x_i^0 + t^*(z_i - x_i^0)$, where

$$t^* = \frac{w_i^q - p^q \cdot x_i^0}{p^q \cdot (z_i - x_i^0)}.$$

So, the second inequality in equation (4) implies $p^q \cdot (z_i - x_i^0) \neq 0$, for $q \geq q^*$. That means that for large q ($\geq q^*$), a_i^q is well defined uniquely and satisfies $\lim_{q \to \infty} a_i^q = x_i^0$. So, the qth term of the imagined sequence $\{x_i^q\}_{q=1}^{\infty}$ can be defined as follows:

$$x_i^q = \begin{cases} \text{an element in } \gamma_i(p^q, w^q), & \text{if } q \leq q^+ \\ a_i^q, & \text{if } q > q^+ \end{cases},$$

where $a_i^q \in \gamma_i(p^q, w^q)$. Once again, the existence of the sequence $\{x_i^q\}_{q=1}^{\infty}$ is only possible under the assumption that potential and actual infinities are the same. QED

In terms of the literature, Proposition 1 generalizes relevant results (e.g., Debreu, 1959, p. 63) by removing unnecessary conditions imposed on the range of the set-valued function γ_i, such as the assumptions of compactness and convexity of X_i.

There are two assumptions in Proposition 1. The reason why the first one on infinities is needed is explained within the proof; and, without it, the conclusion cannot be established, because potential and actual infinities are generally different (Forrest, 2013). As for the second assumption $\leq_i = \leq$, the following Example 1 shows that in general, the conclusion in Proposition 1 does not follow without this assumption.

Example 1. Assume that an economy has only one consumer, such as the economic situation of an individual consumer that he does not have any financial responsibilities for anybody except himself. Assume that his system of values and beliefs demands him to order real numbers by using modular r function, for $r \in \mathbb{R}_+$. That is, this consumer orders real numbers by using $\leq_{mod(r)}$ so that for any $a, b \in \mathbb{R}$, $a \leq_{mod(r)} b$ if and only if the positive reminder of $a \div r \leq$ that of $b \div r$. For example, $4.1 \leq_{mod(4)} 1.2$, because $4.1 \div 4 = 0.1$, while $0.1 \leq 1.2$; and $-1.2 \leq_{mod(4)} -4.1$, because $2.8 \leq 3.9$, where $-1.2 \div 4 = (-4 + 2.8) \div 4 = -1 + 2.8 \div 4$ and $-4.1 \div 4 = (-8 + 3.9) \div 4 = -2 + 3.9 \div 4$.

Consider the following sequence $\{(p^q, w^q)\}_{q=1}^{\infty} \subseteq \mathbb{R}_+^{\ell+1}$ of price-wealth pairs defined by $p^q = p^0$, for a fixed price system $p^0 = (1,1, \dots ,1) \in \mathbb{R}_+^{\ell}$, and $w^q = r - 1/q$, for a fixed price system $p^0 \in \mathbb{R}^{\ell}$, and $q = 1,2, \dots$ It is ready to see that $(p^q, w^q) \to (p^0, r)$, when $q \to \infty$.

Next, let us construct a sequence $\{x^q\}_{q=1}^{\infty}$ of possible consumptions from the consumer's set X as follows: for any $q \in \mathbb{N}$,

$$x^q = \left(x_1^q, x_2^q, \dots , x_\ell^q\right) \in \gamma(p^q, w^q) = \left\{x \in X: p^q \cdot x \leq_{mod(r)} w^q\right\}$$

such that $x_i^q = (r - 1/q)/\ell$, for $i = 1,2, \dots , \ell$. Then it can be readily seen that $x^q \to x^0 = (x_1^0, x_2^0, \dots , x_\ell^0)$ so that $x_i^0 = r/\ell$, for $i = 1,2, \dots , \ell$. However, we have

$$(x_1^0, x_2^0, \dots , x_\ell^0) = \left(\frac{r}{\ell}, \frac{r}{\ell}, \dots , \frac{r}{\ell}\right) \notin \gamma(p^0, w^0)$$

because $\gamma(p^0, w^0) = \left\{x \in X: p^0 \cdot x \leq_{mod(r)} w^0\right\} = \{x \in X: (1,1, \dots ,1) \cdot x = 0\} = \{(0,0, \dots ,0)\}$.

That is, what is shown is that for this particular single consumer economy, when the consumer orders real numbers based on his system of values and beliefs by using $\leq_{mod(r)}$, for any $r \in \mathbb{R}_+$, the set-valued function $\gamma(p, w)$ is not upper semicontinuous from the feasible price-wealth set into the budget set. QED

Consumer's Demand Correspondence

For any given price-wealth pair $(p, w) \in S_i$, consumer i chooses such a consumption $x_i' \in \gamma_i(p, w)$ that $x_i' \gtrsim_i z_i$, for any $\lesssim_i$-comparable $z_i \in \gamma_i(p, w)$. If such consumption x_i' exists, it is known as an i's equilibrium consumption relative to (p, w), denoted by $x_i^{max}(p, w)$. For consumer i to select $x_i^{max} \in \gamma_i(p, w)$, it means that

(a) He selects the quantities of the commodities he will consume;
(b) He decides on the quantities of the kinds of labor he will provide to the market; and
(c) The chosen quantities of commodities and labor jointly form an optimal consumption within his limited wealth.

Because consumptions in X_i are generally not completely comparable by the preference relation $\lesssim_i$, if there is such an equilibrium consumption x_i^{max}, its existence is not generally unique. Hence, for $(p, w) \in S_i$, there are three possibilities: no equilibrium consumption $x_i^{max}(p, w) \in \gamma_i(p, w)$ exists, a unique $x_i^{max}(p, w) \in \gamma_i(p, w)$ exists, and multiple $x_i^{max}(p, w) \in \gamma_i(p, w)$ exist. Define the following subset of S_i

$$S_i^{max} = \{(p, w) \in S_i: \exists x_i^{max}(p, w) \in \gamma_i(p, w) \text{ w.r.t.} \lesssim_i\}, \tag{5}$$

and a set-valued function $\xi_i: S_i^{max} \to X_i$, known as consumer i's demand correspondence (Debreu, 1959), such that for any $(p, w) \in S_i^{max}$,

$$\xi_i(p, w) = \left\{x_i \in X_i: x_i \in \max_{\lesssim_i} \{z_i \in X_i: p \cdot z_i \leq_i w_i\}\right\}, \tag{6}$$

where $\max_{\precsim_i}$ stands for the maximal or maximum operation with respect to the preference relation $\precsim_i$. Hence, the conclusion below comes naturally from these definitions above:

Proposition 2. For any consumptions $x_i^1, x_i^2 \in \xi_i(p, w)$, one of the following holds true:

(i) $x_i^1 \sim_i x_i^2$;
(ii) x_i^1 and x_i^2 are not comparable with respect to the preference relation $\precsim_i$. QED

As for the case when the preference relation $\precsim_i$ is complete, such as the case that $\precsim_i$ becomes complete on a subset A of X_i, although the originally $\precsim_i$ is incomplete, the following holds true.

Proposition 3. If the preference relation $\precsim_i$ is a complete preorder and for $(p^1, w^1), (p^2, w^2) \in S_i^{max}$, there are $x_i^{10} \in \xi_i(p^1, w^1)$ and $x_i^{20} \in \xi_i(p^2, w^2)$ such that $x_i^{20} \prec_i x_i^{10}$, then for any $x_i^1 \in \xi_i(p^1, w^1)$ and $x_i^2 \in \xi_i(p^2, w^2)$, neither $x_i^1 \prec_i x_i^2$ nor $x_i^1 \sim_i x_i^2$ holds true.

Proof. By contradiction, assume that there are certain $x_i^k \in \xi_i(p^k, w^k)$, for $k = 1,2$, such that either (i) $x_i^1 \prec_i x_i^2$ or (ii) $x_i^1 \sim_i x_i^2$. From $x_i^{k0}, x_i^k \in \xi_i(p^k, w^k)$, for $k = 1,2$, it follows that $x_i^{10} \sim_i x_i^1$ and $x_i^{20} \sim_i x_i^2$, because $\precsim_i$ is complete.

If case (i) is true, then we have

$$x_i^{10} \sim_i x_i^1 \prec_i x_i^2 \sim_i x_i^{20},$$

which contradicts to the assumption of $x_i^{20} \prec_i x_i^{10}$. So, case (i) cannot be true.

If case (ii) holds true, then we have

$$x_i^{20} \prec_i x_i^{10} \sim_i x_i^1 \sim_i x_i^2 \sim_i x_i^{20},$$

which means $x_i^{20} \prec_i x_i^{20}$ because of the transitivity of $\precsim_i$, an impossible scenario for complete preorder $\precsim_i$. Hence, case (ii) is an incorrect assumption.

Combining what are argued above, we conclude that neither (i) nor (ii) can be true. QED

Similar to Proposition 3, the following result can be shown:

Proposition 4. If the preference relation $\precsim_i$ is a complete preorder and for $(p^1, w^1), (p^2, w^2) \in S_i^{max}$, there are $x_i^{10} \in \xi_i(p^1, w^1)$ and $x_i^{20} \in \xi_i(p^2, w^2)$ such that $x_i^{20} \sim_i x_i^{10}$, then for any $x_i^1 \in \xi_i(p^1, w^1)$ and $x_i^2 \in \xi_i(p^2, w^2)$, the indifference relation $x_i^2 \sim_i x_i^1$ holds true.

Proof. By contradiction. Assume that there are $x_i^1 \in \xi_i(p^1, w^1)$ and $x_i^2 \in \xi_i(p^2, w^2)$ such that $x_i^1 \nsim_i x_i^2$. Then there are two possibilities: (i) $x_i^1 \succ_i x_i^2$; or (ii) $x_i^1 \prec_i x_i^2$. However, according to Proposition 3, if either (i) or (ii) holds true, then $x_i^{20} \sim_i x_i^{10}$ cannot hold true. This end contradicts the given conditions. Hence, the assumption that $x_i^1 \nsim_i x_i^2$, for some $x_i^k \in \xi_i(p^k, w^k)$, for $k = 1,2$, cannot hold true. QED

For $(p^1, w^1), (p^2, w^2) \in S_i^{max}$, consumer i prefers the price-wealth pair (p^1, w^1) to the pair (p^2, w^2), if there are $x_i^1 \in \xi_i(p^1, w^1)$ and $x_i^2 \in \xi_i(p^2, w^2)$ such that $x_i^2 \prec_i x_i^1$. If, instead, there are such consumptions $x_i^k \in \xi_i(p^k, w^k)$, $k = 1,2$, that $x_i^1 \sim_i x_i^2$, then the price-wealth pairs (p^1, w^1) and (p^2, w^2) are said to be indifferent.

Proposition 5. If the preference relation $\precsim_i$ is a complete preorder, then the preference relation, as just defined above on S_i^{max}, is also a complete preorder.

This conclusion follows directly from Propositions 3 and 4. And without causing confusion, in this case, the preference relation defined on S_i^{max} will also be written as $\precsim_i$.

The following reasoning illustrates that when the preference relation $\precsim_i$ is not a complete preorder, then the preference relation defined above on S_i^{max} might not be well defined. Specifically, there might be price-wealth pairs (p^1, w^1) and $(p^2, w^2) \in S_i^{max}$ such that there are $x_i^1, x_i^{10} \in \xi_i(p^1, w^1)$ and $x_i^2, x_i^{20} \in \xi_i(p^2, w^2)$ such that

$$x_i^1 \prec_i x_i^2 \text{ and } x_i^{20} \prec_i x_i^{10}.$$

For this end to hold, we only need to make sure to select $x_i^1, x_i^{10} \in \xi_i(p^1, w^1)$ and $x_i^2, x_i^{20} \in \xi_i(p^2, w^2)$ so that x_i^1 and x_i^{10} are $\precsim_i$-incomparable, and so are x_i^2 and x_i^{20}.

The Total Demand Correspondence

If for the preference relation $\precsim_i$ there is such a subset $X_i^* \subseteq X_i$ that for any x_i^1 and $x_i^2 \in X_i^*$, $x_i^1 \neq x_i^2$ implies that $[x_i^1] \neq [x_i^2]$ and $X_i = \cup_{x_i \in X_i^*}[x_i]$, then this subset X_i^* is referred to as a set of (consumer i's) preference representations. The idea behind such a set X_i^* is that when the preference relation $\precsim_i$ is only reflexive without being complete and transitive, it cannot generally be utility representable. For the incompleteness of some $\precsim_i$, see, for example, Bosi and Herden (2012), Nishimura and Ok (2016), for the nontransitivity of certein $\precsim_i$, see, for example, Birnbaum and Gutierrez (2007), Forrest, Darvishi et al., (to appear), Tversky (1969). Therefore, in real-life applications of relevant economic theories, an appropriate X_i^* can be chosen to play the role as that a real-number valued utility function has conventionally played (Mas-Collel et al., 1995).

For a chosen set $X_i^* \subseteq X_i$ of consumer i's preference representations, let $u_i: X_i \to X_i^*$ be the canonical utility function of consumer i such that for any consumption $x_i \in X_i$, $u_i(x_i) = x_i^* \in X_i^*$, if $x_i \in [x_i^*]$. It is shown (Forrest, Darbishi et al., to appear) that if $\precsim_i$ is a complete preorder on X_i, the aforementioned subset $X_i^* \subseteq X_i$ exists.

For each maximal chain X_i^{max} in X_i^*, the u_i-preimage of the chain X_i^{max} is equal to

$$u_i^{-1}(X_i^{max}) = \cup \{[x_i^*]: x_i^* \in X_i^{max}\}.$$

In the rest of this paper, assume that a set X_i^* of (consumer i's) preference representations exists and is chosen, and for any maximal chain X_i^{max} in X_i^* a utility function $u_i^{max}: u_i^{-1}(X_i^{max}) \to \mathbb{R}$ also exists and is fixed.

Proposition 6. If consumer i's ordering $\leq_i$ of real numbers satisfies the condition of positive multiplicativity, that is, for any scalar $\alpha > 0$ and $a, b \in \mathbb{R}$, $a \leq_i b \to \alpha a \leq_i \alpha b$, then for any $t \in \mathbb{R}_+$, $\xi_i(tp, tw) = \xi_i(p, w)$.

Proof. From equation (6), it follows that

$$\xi_i(tp, tw) = \left\{x_i \in X_i: x_i \in \max_{\precsim_i}\{z_i \in X_i: tp \cdot z_i \leq_i tw_i\}\right\}.$$

Because the ordering $\leq_i$ satisfies the condition of positive multiplicativity, $tp \cdot z_i \leq_i tw_i$ is equivalent to $p \cdot z_i \leq_i w_i$. Hence, the previous expression is equal to

$$\left\{x_i \in X_i: x_i \in \max_{\precsim_i}\{z_i \in X_i: p \cdot z_i \leq_i w_i\right\} = \xi_i(p, w).$$

That is, we have shown $\xi_i(tp, tw) = \xi_i(p, w)$, for any $t \in \mathbb{R}_+$. QED

The condition of positive multiplicity evidently holds true for the conventional ordering of real numbers. However, the following example shows that it does not hold true generally for a randomly chosen ordering of real numbers.

Example 2. Here a situation is constructed to show that positive multiplicativity is not generally satisfied by any ordering of real numbers. In particular, the condition of positive multiplicativity is not satisfied by the order relation $\leq_{mod(4)}$ does not satisfy the. In fact, we have

$$1 \leq_{mod(4)} 2 \nrightarrow 2 \cdot 1 \leq_{mod(4)} 2 \cdot 2$$

where the left-hand side is actually $2 \cdot 1 = 2 \geq_{mod(4)} 2 \cdot 2 = 0$ = the right-hand side. QED

For a price-wealth pair $(p, w) \in \mathbb{R}^{\ell+m}$, if $(p, w) \in \bigcap_{i=1}^{m} S_i^{max}$, meaning that for each $i = 1,2, \dots, m$, there is at least one maximal consumption $x_i^{max} \in \gamma_i(p, w)$, define the following set-valued, partial function $\xi: \mathbb{R}^{\ell+m} \to \sum_{i=1}^{m} X_i = \{x = x_1 + x_2 + \cdots + x_m : x_i \in X_i, i = 1,2, \dots, m\}$:

$$\xi(p, w) = \sum_{i=1}^{m} \xi_i\,(p, w), \tag{7}$$

such that the domain of ξ is $\bigcap_{i=1}^{m} S_i^{max}$ and that for each $x = x_1 + x_2 + \cdots + x_m \in \xi(p, w)$, $x_i = x_i^{max} \in \xi_i(p, w)$ is a maximal consumption of consumer i. This function ξ is referred to as the total demand correspondence (Debreu, 1959). Both Proposition 6 and equation (7) jointly imply that

Proposition 7. For any $(p, w) \in \bigcap_{i=1}^{m} S_i^{max}$ and any scalar $t \in (0, +\infty)$, $\xi(tp, tw) = \xi(p, w)$. QED

Proposition 8. For a given price-wealth pair $(p, w) \in S_i$, x_i^* is a maximal element in $\gamma_i(p, w)$ with respect to the preference relation $\precsim_i$, if and only if x_i^* minimizes the expenditure $p \cdot x_i$ on the set $\{x_i \in X_i : x_i \succsim_i x_i^*\}$.

Proof. (⇒) Assume that $x_i^* \in \max_{\precsim_i} \gamma_i(p, w)$. From equation (2), it follows that

$$\begin{aligned} x_i^* \quad &\in \max_{\precsim_i}\{x_i \in X_i : p \cdot x_i \leq_i w_i\} \\ &= \min_{\precsim_i}\{x_i \in X_i : p \cdot x_i \geq_i w_i\} \\ &= \min{}_{x_i \in X_i, p \cdot x_i \geq_i w_i}\{x_i \in X_i : x_i \succsim_i x_i^*\}. \end{aligned}$$

That is, x_i^* minimizes the expenditure $p \cdot x_i$ on the set $\{x_i \in X_i : x_i \succsim_i x_i^*\}$.

(⇐) The argument for this part is similar to the reasoning above except that we move forward in the opposite direction. QED

Relationship between Preferences and Order of Real Numbers

One can readily see that both $\precsim_i$ and $\leq_i$ are defined on consumer i's system of values and beliefs, although the preference relation $\precsim_i$ can be temporarily influenced by peers and altered slightly by peer pressures (Hu et al., 2021; Li, et al., 2023; Mani et al., 2013). In other words, because of their common roots, in some measure $\precsim_i$ and $\leq_i$ cannot be inconsistent with each other. One way to describe such consistency between these orders, let us adopt the following Axioms from Debreu (1959).

Axiom 3. For any price-wealth pair $(p. w) \in S_i$, any consumption $x_i \in X_i$, and a chosen $x_i^* \in X_i$, $p \cdot x_i \leq_i w_i$ implies $x_i \precsim_i x_i^*$.

Axiom 4. For any price-wealth pair $(p. w) \in S_i$, any consumption $x_i \in X_i$, and a chosen $x_i^* \in X_i$, $x_i \succsim_i x_i^*$ implies $p \cdot x_i \geq_i w_i$.

Preference relation $\precsim_i$ is said to be continuous (Forrest, Darvishi et al., to appear), if for any maximal chain X_i^{max} in X_i^*, and for each $x_i' \in u_i^{-1}(X_i^{max})$, the following sets are closed in $u_i^{-1}(X_i^{max})$:

$$\{x_i \in u_i^{-1}(X_i^{max}) : x_i \precsim_i x_i'\} \text{ and } \{x_i \in u_i^{-1}(X_i^{max}) : x_i \succsim_i x_i'\}. \tag{8}$$

The relation $\precsim_i$ is said to be additively conserved, if for any consumptions $a_i^j, b_i^j \in X_i$, $j = 1,2$,

$$a_i^1 \precsim_i b_i^1 \text{ and } a_i^2 \precsim_i b_i^2 \ \rightarrow a_i^1 + a_i^2 \precsim_i b_i^1 + b_i^2, \tag{9}$$

where the sign $\precsim_i$ becomes $\prec_i$ in the consequence, if $\prec_i$ appears in at least one of the two antecedents. Accordingly, the relation $\precsim_i$ is said to be positively multiplicative, if for any consumptions $x_i^1, x_i^2 \in X_i$ and any scalar $\alpha > 0$,

$$x_i^1 \precsim_i x_i^2 \ \rightarrow \alpha x_i^1 \precsim_i \alpha x_i^2,$$

where the sign $\precsim_i$ will become $\prec_i$ in the consequence, if $\prec_i$ appears in the antecedent. And, $\precsim_i$ is said to be asymptotically preserves preference preordering, if for each sequence $\{x_i^q\}_{q=1}^{\infty} \subseteq X_i$, satisfying $x_i^q \succsim_i x_i^0$ (respectively, $x_i^q \precsim_i x_i^0$), for each $q \in \mathbb{N}$ and some $x_i^0 \in X_i$, $\lim_{q\to\infty} x_i^q \succsim_i x_i^0$ (respectively, $\lim_{q\to\infty} x_i^q \precsim_i x_i^0$), whenever the limit exists.

Proposition 9. If the following conditions hold true, then Axiom 4 implies Axiom 3.

(i) $w_i \neq_i \min_{z_i \in X_i} p \cdot z_i$,
(ii) preference relation $\precsim_i$ satisfies the conditions of additive conservation and positive multiplicativity, and
(iii) consumer i's consumptions asymptotically preserve preference relation $\precsim_i$.

Proof. For any price-wealth pair $(p.w) \in S_i$, any consumption $x_i \in X_i$, and a fixed $x_i^* \in X_i$, assume that $x_i \succsim_i x_i^*$ implies $p \cdot x_i \geq_i w_i$. Equivalently, $p \cdot x_i <_i w_i$ implies $x_i^* \succ_i x_i$. We need to show that for any consumption $x_i \in X_i$, if $p \cdot x_i \leq_i w_i$, then $x_i \precsim_i x_i^*$.

Axiom 4 implies that for any consumption $x_i \in X_i$, $p \cdot x_i <_i w_i$ implies $x_i \prec_i x_i^*$. For the rest of this proof, we focus on showing that for any consumption $x_i \in X_i$, $p \cdot x_i =_i w_i$ implies $x_i \precsim_i x_i^*$. To this end, because $w_i \neq_i \min_{z_i \in X_i} p \cdot z_i$, there is a consumption $x_i^1 \in X_i$ such that $x_i^1 \neq x_i$, and $p \cdot x_i^1 <_i w_i$.

For any scalar $\alpha \in (0,1)$, define $z_i(\alpha) = \alpha x_i^1 + (1-\alpha)x_i$. From $p \cdot x_i^1 <_i w_i$ and $p \cdot x_i =_i w_i$, the condition of positive multiplicativity guarantees that $p \cdot (\alpha x_i^1) <_i \alpha w_i$ and $p \cdot (1-\alpha)x_i =_i (1-\alpha)w_i$. So, the condition of additive conservation implies

$$p \cdot z_i(\alpha) = p \cdot \alpha x_i^1 + p \cdot (1-\alpha)x_i <_i \alpha w_i + (1-\alpha)w_i = w_i.$$

So, Axiom 4 implies that $z_i(\alpha) \prec_i x_i^*$ and that for any natural number q, $z_i(q^{-1}) = q^{-1}x_i^1 + (1-q^{-1})x_i \rightarrow x_i$. So, the asymptotical preservation of consumer i's preference implies that $x_i = \lim_{q\to\infty} z_i(q^{-1}) \precsim_i x_i^*$. QED

In terms of the literature, the conclusion that Axiom 4 implies Axiom 3 was established under a different set of conditions. In particular, instead of conditions (ii) and (iii) in Proposition 9, Debreu (1959) requires that X_i is convex, and $\precsim_i$ is a continuous and complete preorder. Therefore, a generalization of Debreu's work is established here, because in this paper the preference $\precsim_i$ is not generally assumed to be a complete preorder. As for the conditions listed in (ii) and (iii) in Proposition 9, Examples 3 and 4 below demonstrate that (a) in general, the preference relation $\precsim_i$ does not necessarily satisfy the condition of additive conservation, and (b) not every preference relation $\precsim_i$ is asymptotically preserving. And similar to Example 2, one can readily see that not all preorders satisfy the condition of positive multiplicativity.

Example 3. Assume that consumer i's system of values and beliefs preorders the quantities of a particular commodity h by referring to the mod4 function so that for any two real numbers x and y, $x \prec_i y$ if and only if $x(\text{mod}4) < y(\text{mod}4)$. Let $x_i^1, x_i^2, x_i^3 \in X_i$ be three consumptions such that

$$x_{ik}^1 = x_{ik}^2 = x_{ik}^3, k = 1, 2, \ldots, \ell, k \neq h,$$

and

$$x_{ih}^1 = 2, x_{ih}^2 = 3 \text{ and } x_{ih}^2 = 1.$$

Then, we have $x_i^1 \precsim_i x_i^2$ and $x_i^3 \precsim_i x_i^3$. However, instead of $x_i^1 + x_i^3 \precsim_i x_i^2 + x_i^3$, we have

$$x_i^1 + x_i^3 \succsim_i x_i^2 + x_i^3,$$

because

$$x_{ik}^1 + x_{ik}^3 = x_{ik}^2 + x_{ik}^3, k = 1, 2, \dots, \ell, k \neq h,$$

and

$$x_{ih}^1 + x_{ih}^3 = 3 \succsim_i x_{ih}^2 + x_{ih}^3 = 3 + 1 \ =_{mod4} 0.$$

That is, the specifically defined $\precsim_i$ is not additively conserved. QED

Example 4. Let us continue to employ the preference relation $\precsim_i$, defined in the previous example. And, define a sequence $x_i^1, x_i^2, \dots, x_i^q, \dots \in X_i$ of possible consumptions for consumer i such that

$$x_{ik}^q = x_{ik}^1, k = 1, 2, \dots, \ell, k \neq h, q = 1,2, \dots \tag{10}$$

and

$$x_{ih}^q = 3 + \frac{q}{q+1}, q = 1,2, \dots \tag{11}$$

Then, it is ready to see that $x_i^q \to x_i^0$, as $q \to \infty$, where $x_{ik}^0 = x_{ik}^1, k = 1, 2, \dots, \ell, k \neq h$, and $x_{ih}^0 = 0$, which is equal to $4\ (mod4)$.

Define x_i^{low} as follows: $x_{ik}^{low} = x_{ik}^1, k = 1, 2, \dots, \ell, k \neq h$, and $x_{ih}^{low} = 3$. Then, equations (10) and (11) imply that

$$x_i^q \succsim_i x_i^{low} \text{ and } \lim_{q\to\infty} x_i^q = x_i^0 \prec_i x_i^{low}.$$

That is, the specifically defined preference relation $\precsim_i$ is not asymptotically conserved. QED

The set X_i of consumer i's possible consumptions is said to be convex with respect to $\precsim_i$ (Debreu, 1959, p. 60; Forrest, Tiglioglu et al., 2022) or $\precsim_i$ is said to be convex, if X_i is convex, as a subset of $\mathbb{R}^\ell$, and for any distinct consumptions $x_i^1, x_i^2 \in X_i$ and arbitrary scalar $\alpha \in (0,1)$,

$$x_i^1 \prec_i x_i^2 \to x_i^1 \prec_i \alpha x_i^2 + (1-\alpha) x_i^1. \tag{12}$$

One consumption $x_i \in X_i$ is said to be satiation for consumer i (Mas-Collel et al., 1995), if for any $y_i \in X_i$, $y_i \precsim_i x_i$. It is ready to see that if consumer i has incomparable consumptions, then there might be several incomparable satiation consumptions in X_i simultaneously.

Proposition 10. If both X_i and $\precsim_i$ are convex, $x_i^* \in X_i$ is not a satiation consumption, and consumer i's consumptions asymptotically preserve preference relation $\precsim_i$, then Axiom 3 implies Axiom 4.

Proof. For any price-wealth pair $(p.w) \in S_i$, any consumption $x_i \in X_i$, and a chosen $x_i^* \in X_i$, Axiom 3 is equivalent to $x_i \succ_i x_i^* \to p \cdot x_i >_i w_i$. Let $x_i \in X_i$ satisfy $x_i \succsim_i x_i^*$, which can be split into two cases: $x_i \succ_i x_i^*$ and $x_i \sim_i x_i^*$. Axiom 3 guarantees that the former case leads to the desired conclusion $p \cdot x_i >_i w_i$ or $p \cdot x_i \geq_i w_i$.

For the second case $x_i \sim_i x_i^*$, because $x_i^* \in X_i$ is not a satiation consumption, there is a consumption $x_i^1 \in X_i$ such that $x_i^1 \succ_i x_i^*$. So, for any scalar $\alpha \in (0,1)$, the convexity of X_i implies that $\alpha x_i^1 + (1-\alpha)x_i \in X_i$; and the convexity of $\precsim_i$ guarantees that $\alpha x_i^1 + (1-\alpha)x_i$ and x_i are comparable in terms of $\precsim_i$ such that $x_i^* \sim_i x_i \prec_i z_i(\alpha) = \alpha x_i^1 + (1-\alpha)x_i$. So, Axiom 3 implies that

$$p \cdot z_i\left(\frac{1}{n}\right) >_i w_i, \text{for } n = 2,3,4,\ldots \tag{13}$$

From $z_i\left(\frac{1}{n}\right) \to x_i$, the asymptotic preservation of the preference relation $\precsim_i$ and equation (13) guarantee that $p \cdot x_i \geq_i w_i$. QED

Comparing to what has been established in the literature (e.g., Levin & Milgrom, 2004; Mas-Collel et al., 1995), when the preference relation $\precsim_i$ is no longer assumed to be a complete preorder, the convenient fact that $p \cdot x_i$ is a continuous function in x_i cannot be readily employed (e.g., Dubra & Ok, 2002; Ok, 2002; Nishimura & Ok, 2016; Bosi & Herden, 2012) in the proof of Proposition 10, as Example 4 demonstrates.

Proposition 11. For given $(p,w) \in S_i^{max}$ and $x_i^* \in \xi_i(p,w)$, if the following hold true, then $p \cdot x_i^* = w_i$.

- X_i is convex, as a subset of $\mathbb{R}^\ell$, and is convex with respect to $\precsim_i$,
- x_i^* is not a satiation consumption,
- consumer i's consumptions asymptotically preserve preference relation $\precsim_i$,

Proof. From $x_i^* \in \xi_i(p,w)$, it follows that $p \cdot x_i^* \leq_i w_i$. To establish the desired equality, it suffices to show that $p \cdot x_i^* \geq_i w_i$. To this end, let $X_i^* \subseteq X_i$ be a chosen subset of consumer i's preference representations, $u_i: X_i \to X_i^*$ the canonical utility function, and X_i^{max} a maximal chain in X_i^* such that $x_i^* \in u_i^{-1}(X_i^{max})$.

Hence, for any $x_i \in u_i^{-1}(X_i^{max})$, if $p \cdot x_i \leq_i w_i$, then $x_i \in \gamma_i(p,w)$ and therefore $x_i \precsim_i x_i^*$. That is, Axiom 3 holds true on $u_i^{-1}(X_i^{max})$, which, from Proposition 10, implies that Axiom 4 holds true. That is, $p \cdot x_i^* \geq_i w_i$. QED

Proposition 12. Assume that each infinity can be actually (not potentially) achieved. If $u_i^{-1}(X_i^{max})$ is a connected subset of $\mathbb{R}^\ell$, for each maximal antichain $X_i^{max} \subseteq X_i^*$, and the preference relation $\precsim_i$ is continuous on X_i, then $S_i^{max} = S_i$.

Proof. For each maximal antichain $X_i^{max} \subseteq X_i^*$, let us choose a continuous utility function $u_i^{max}: u_i^{-1}(X_i^{max}) \to \mathbb{R}$. The existence of u_i^{max} is confirmed by the famous Debreu (1959), where the original proof is valid only with the assumption that each infinity can be actually (not potentially) achieved (for details, see the proof of Proposition 9).

For each price-wealth pair $(p,w) \in S_i$, consumer i chooses a maximum in $u_i^{-1}(X_i^{max}) \cap \gamma_i(p,w)$ in terms of $\precsim_i$, which reflects the principles held in his system of values and beliefs. That is, he maximizes u_i^{max} on $u_i^{-1}(X_i^{max}) \cap \gamma_i(p,w)$, which is non-empty and compact, because of the Lower Boundedness Axiom (Axiom 1) and the definition of γ_i. Therefore, the real-number valued utility function u_i^{max} actually reaches its maximum on $u_i^{-1}(X_i^{max}) \cap \gamma_i(p,w)$. In other words, there is a non-empty subset of maximal consumptions in $\gamma_i(p,w)$. That is, $(p,w) \in S_i^{max}$. Hence, the equality $S_i^{max} = S_i$ has been shown. QED

Comparing to the literature, this result generalizes the corresponding result (Debreu, 1959, p. 72) by removing the one imposed condition: the set X_i of consumption is a compact subset in $\mathbb{R}^\ell$.

A FEW FINAL WORDS

This paper embeds a consumer's set X_i of all possible consumptions in a Euclidean space $\mathbb{R}^\ell$, while removing the unrealistic assumption that a consumer's consumption preferences are complete (e.g., Hervés-Beloso & Cruces, 2019; Levin & Milgrom, 2004; Mas-Collel et al., 1995). On such bases, this research revisits part of the prevalent consumer theory regarding a consumer's budget set and demand correspondence and shows, among other conclusions, that

- Only when a consumer's order of real numbers is the same as the conventional one, the budget set function γ_i is continuous at the price-wealth pair $(p^0, w^0) \in S_i$ satisfying $w_i^0 \neq \min_{x_i \in X_i} p^0 \cdot x_i$ (Proposition 1 and Example 1).
- If consumer i's ordering $\leq_i$ of real numbers satisfies the condition of positive multiplicativity, then this consumer i's demand correspondence is homogenous of degree zero in price and in wealth. That is, for any $t \in \mathbb{R}_+$, $\xi_i(tp, tw) = \xi_i(p, w)$ (Proposition 6).
- The conditions of additive conservation and asymptotic preservation are not generally satisfied by preference relations (Examples 3 and 4).
- If each maximal chain $U \subseteq X_i$ is connected in $\mathbb{R}^\ell$ and preference relation $\precsim_i$ is continuous on X_i, then for each feasible price-wealth pair (p, w) there is at least one equilibrium consumption $x_i^{max}(p, w)$ (Proposition 12).

Highlighted by these results, this paper necessarily introduces several unconventional concepts, such as consumer-specific order of real numbers, positive multiplicativity, additive conservation, and asymptotic preservation. It then confirms under what conditions some of the previously known properties continue to hold true. At the same time, this paper investigates issues never before faced so that brand new conclusions are established.

Other than its theoretical contribution, as outlined above, this paper can also be seen as a small part of a much larger effort of developing a new consumer theory for the purpose of producing more tangible economic values than possible by the current, prevalent theory. Such need has been loudly called for by Paul Krugman (*New York Times*, 2009-09-02), Paul De Grauwe (*Financial Times*, 2009-07-21), and others.

For future research, there are evidently many important questions still left open. For example, if a preference relation $\precsim_i$ is not a complete preorder, under what conditions will the relation $\precsim_i$ on S_i^{max}, as given in Section 3.2, be well defined? What will be the form of Proposition 1 if $\leq_i$ is not the same as $\leq$? Under what conditions does the preference relation $\precsim_i$ have a set X_i^* $(\subseteq X_i)$ of preference representations, when $\precsim_i$ is not a complete preorder, as mentioned at the start of Section 3.3? In some measure the binary relations $\precsim_i$ and $\leq_i$ cannot be inconsistent with each other, as stated in Section 3.4. Can such an unspecified measure be identified for each given system of values and beliefs?

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IDENTIFYING CRITICAL FACTORS THAT IMPACT LEARNING ANALYTICS ADOPTION BY HIGHER EDUCATION FACULTY

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ABSTRACT

Higher education institutions (HEI) invest heavily in learning analytics as a compliment to their existing suite of technologies used to enhance the pedagogical practices of instructors. With promises of reduced student dropout rates, improved student outcomes, better course pedagogy, and backed by pressures of assessment and accountability, learning analytics is being trumpeted as the next best solution to our educational woes. However, instructors have been slow, if not resistant, to adopt learning analytics. The following paper demonstrates how the technology-pedagogy-content knowledge framework (TPACK) can be used to extend traditional technology adoption models to include professional identity expectancy in an effort to explain intention to use behavior. A quantitative analysis of 222 United States based survey respondents is used to inform results. The results support effort expectancy, pedagogical expectancy, and professional identity expectancy to be key factors of willingness to adopt learning analytics. These results may inform additional research into the influence of professional identity expectancy on technology adoption as well as research, development, and marketing opportunities within the consumer space of learning analytics tools.

INTRODUCTION

A data revolution is upon us. For-profit businesses have successfully capitalized on using vast amounts of data and sophisticated analytical tools to drive huge profits and tremendous market share (Thirathon, Wieder, Matolcsy, & Ossimitz, 2017; Davenport, 2006; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Choo, et al., 2006). It is clear that organizations, as they always have, seek to make good strategic and operational decisions. However, the processes and tools available to make these decisions is rapidly changing. Organizations are beginning to adopt a culture of analytics (Gupta & George, 2016) and it becomes an interesting challenge to understand where higher education institutions (HEI) stand in the landscape of internalizing learning analytics.

While a multitude of different definitions of learning analytics have evolved over the years, the definition provided at the inaugural international conference on LA in 2011 provides a sound base (Siemens, Long, Gasevic, & Conole, 2010); *"The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs."*. The use of the word 'optimizing' is noteworthy. LA imparts an economic lens on the educational process. It is possible that this economic lens will run orthogonal to instructors' traditional view of education and to their own professional identity. Such a belief may influence a higher education faculty member's willingness to adopt LA into their pedagogical practices.

HEIs are slowly adopting a culture of LA but there is not consensus on the value and effectiveness of the tools and practices that make up the culture. There exists tremendous variability in how individual faculty members interface with LA as it relates to adoption, sense making, and influence on professional identity (Avella, Kebritchi, Nunn, & Kanai, 2016). A demand for more research to understand the beliefs of users of the LA systems exists (Ferguson, et al., 2016). An important research agenda is to better understand key constructs that serve to enable an individual higher education faculty member to be willing to adopt learning analytics into their daily practice. LA in part is just one of the latest manifestations of new technologies. Most LA are embedded into existing learning management systems which are already adopted on a very large scale. Given that learning analytics is just a different flavor of technology, it is easy to assume that existing technology adoption models will seamlessly apply. But LA have characteristics which differentiates itself from other typical educational technology. First, LA is not a standalone device like a graphing calculator or an interactive smartboard. It is not just one technology, but an amalgamation of many technologies. Second, there is an inherent feedback loop incorporated into the design of LA. LA are intended to evaluate a given pedagogical experience, transparently report on that experience, and then be interpreted by the stakeholders in the pedagogical experience in order to inform the future direction of the experience. And lastly, LA focus multiple aspects of pedagogy that most educational technologies do not. Specifically, learning analytics brings into focus technical knowledge, pedagogical knowledge and discipline or content knowledge. The LA research corpus lacks research placing the higher education faculty stakeholder front and center. Certainly, faculty buy-in plays a large role in LA adoption (Dawson, et al., 2018; Kaliisa, 2021). This guides the following fundamental research questions.

RQ1: What are the emergent enablers to a higher education faculty member's willingness to adopt learning analytics into their professional practice?
RQ2: What role does the concept of professional identity expectancy fill in determining a higher education faculty member's willingness to adopt learning analytics?

The purpose of this quantitative theory testing study is to examine how extent technology adoption theory models may be adjusted to incorporate the influence of professional identity into the specific adoption of learning analytics. Additionally, the study is intended to more clearly understand the enablers that exert a positive influence on the willingness of fulltime higher education faculty to adopt LA into their professional practice. Of particular research interest is fulltime faculty that teach undergraduate courses at universities that offer traditional two-year associate degrees, four-year bachelor degrees or advanced professional level doctorate degrees. The research study fills a gap in the learning analytics research literature as it pertains to adoption and perceptions of LA from higher education faculty. The research also serves the practitioner community by offering insight into challenges and opportunities of learning analytics usage and adoption within HEIs.

LITERATURE REVIEW AND RESEARCH MODEL

Literature Review

HEIs are interesting organizations to study due to the relatively new exploration of analytics and the wide diversity of the analytics being used (Avella, Kebritchi, Nunn, & Kanai, 2016). A number of years ago, a call to arms was put forth to HEIs to migrate beyond traditional uses of analytics in management of enrollment, retention and alumni relations and explore the integration of analytics in the pure academic and learning space (Campbell, Deblois, & Oblinger, 2007). Early exploration of this space pushed HEIs to invest in analytics that provided true measurement of institutional goals (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). HEIs don't only use analytics to improve revenue or profit margins (traditionally viewed as business analytics), they also use analytics within the curriculum landscape (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). It is within the curriculum landscape where things get interesting as the broad field of analytics narrows to learning analytics (LA). In the ensuing years, the field of LA begins to take shape. The first annual international conference in learning analytics and knowledge was held in 2010. The first edition of the Journal of Learning Analytics was published in 2013. In the inaugural issue, Siemens (2014) points out that higher education is comparatively late to the analytics game but their presence is important as data continues to play a key role in how learning transpires and how faculty make decisions within the learning context.

LA research conducted to date has primarily focused on LA design (Bakharia, et al., 2016; Greller & Drachsler, 2012), data visualization design (Echeverria, et al., 2018), or use cases that support using LA as a retention or early warning system (Gasevic, Dawson, & Siemens, 2015). Literature reviews in LA also show emerging concerns over data ownership, privacy, and ethics (Viberg, Hatakka, Balter, & Mavroudi, 2018; Avella, Kebritchi, Nunn, & Kanai, 2016). While there exists a generally shared belief in the positive impact and potential of learning analytics, institutions and individual faculty show surprisingly slow (perhaps even resistant) adoption rates (Herodotou, et al., 2017; Alzahrani, 2023). Determining factors that influence this resilience poses an interesting research challenge. An important perspective is that LA represents a disruptive influence on the current culture in HEI (Avella, Kebritchi, Nunn, & Kanai, 2016). LA push the barriers of accountability and assessment (Sergis & Sampson, 2017). While prior LA research projects point to the importance of the stakeholders and specifically the individual faculty member (Campbell, Deblois, & Oblinger, 2007; Kaliisa, 2021), a research gap exists as it pertains to the perspective of the individual faculty member. Campbell, et al., (2007) specifically point to the importance of faculty in the process of utilizing learning analytics*, "Faculty are key to "interventions" … For some faculty, analytics may provide a valuable insight into which students are struggling or which instructional approaches are making the greatest impact."*. The faculty perspective gap opens an opportunity for further study. Specifically, it becomes interesting to explore the various personal and organizational constructs that affect the willingness of a higher education faculty member to adopt LA. The existing body of LA research does not sufficiently represent the perspective of the higher faculty member. This perspective is critical in understanding how various constructs may threaten or enable willingness to adopt LA.

Theoretical Foundation

The true underlying issues with LA in higher education are adoption and integration. Similar research that focuses on the phenomenon of learning management system integration within secondary schools (Towne, 2018), reveals several theories applicable to this research. The phenomenon of LA usage by higher education faculty in part represents an example of technology adoption. As such, theories such as the Technology Adoption Model (TAM) (Davis F. , 1989) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) provide a good base. While TAM and UTAUT are historically widely used theories, they continue to prove helpful in understanding why certain technologies are adopted and why certain technologies are not. UTAUT represents a valuable theory as this theory specifically addresses concepts of performance expectancy, effort expectancy, and social influence. However, TAM or UTUAT as an overarching theory base lack specificity to the education domain and the perspective of the higher education faculty member. The higher education faculty member is assumed to be a rational actor in the culture of analytics. Psychology based theories such as the Theory of Reasoned Action (TRA) (Sheppard, 1988) or the Theory of Planned Behavior (TPB) (Ajzen, 1991) are reasonable theory bases to draw from. Yet here again, these theories fail to address the unique characteristics of HEIs. Cognitive science theories on decision-making such as Rational Choice Theory (Tversky & Kahneman, 1981) were also considered but fell short against the strength of the Technological Pedagogical Content Knowledge Framework (TPACK) (Mishra & Koehler, 2006). Higher education faculty are expected to incorporate new tools and new processes into their day-to-day workflow. Their ability to leverage LA tools and information effectively may hinge in large part on both their self-identified analytical skillsets and their personal beliefs in learning new ways to evaluate student learning. TPACK provides a strong theoretical foundation for examining LA adoption. Mishra and Koehler (2006) introduced TPACK in order to provide a stronger theoretical framework for the adoption and usage of educational technology. TPACK seeks to explain the complex interactions of three distinct knowledge areas; technology, pedagogy and content. These interactions exist on a binary level between two distinct knowledge areas and on a multifaceted level where all three knowledge areas come together as one. Using this conceptual framework as a theory base, willingness to adopt can be explored along the same three basic vectors. Technology knowledge can be framed as efficacy with LA technologies. Pedagogy knowledge relates to how an individual higher education faculty member reconciles LA against their pedagogical practices. Content knowledge speaks directly to the specific disciplinary knowledge that a faculty member possesses. Content knowledge can be extended to include beliefs about what is required to be a professional within a respective discipline. Lastly, willingness to adopt a certain educational technology can be examined by the manner in which all three forces come together. The TPACK framework is visually depicted in Figure 1 (Koehler, Mishra, & Cain, 2013). The framework establishes seven core knowledge constructs that work in concert with each other to help explain technology integration in education; Technology Knowledge (TK), Content Knowledge (CK), Pedagogy Knowledge (PK), Technology-Content Knowledge (TCK), Technology Pedagogy Knowledge (TPK), Content-Pedagogy Knowledge (CPK) and Technology-Content-Pedagogy Knowledge (TPACK).

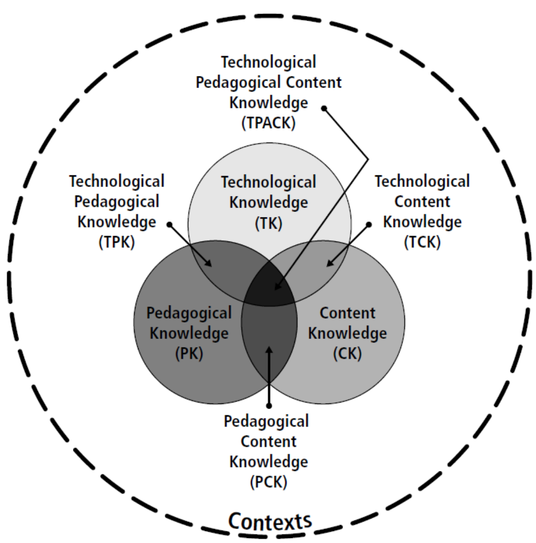

Figure 1. TPACK Framework

Research Model

Effective integration of LA into professional practice requires the higher education faculty member to embody certain knowledge and skills. This is the heart of the TPACK framework used as the theoretical base for this research. The foundational technical skills and knowledge for LA reside in analytical technologies and tools and data cycle literacy. Dunn, et al., explore data tools and technology as well as data literacy in their research on teacher efficacy and anxiety in the data-driven decision process (Dunn, Airola, Lo, & Garrison, 2013). Efficacy has also played a key role in major technology adoption theories such as TAM and UTAUT (Davis F. , 1986; Venkatesh, Morris, Davis, & Davis, 2003). While efficacy in the tools and technology of LA is important, an understanding of the foundational data life cycle also has value. Clow (2012) envisions the conceptual framework of LA as a cycle. Learners are at the top of this cycle and while a cycle does not technically have a true starting position, the framework assumes learners initiate the LA cycle. Learners create data that is collected, measured and analyzed through metrics. The metrics lead to interventions with learners. In turn, learners create new data and the cycle continues. The central concept of this data model is the existence of an inherent cycle in LA; a built-in feedback loop within the teaching-learning process.

Pedagogical knowledge from TPACK can be envisioned as the degree to which the higher education faculty member perceives the goals and purpose of LA run congruent to their specific pedagogical practices performed in a given instructional setting. The pedagogical alignment can be envisioned along two basic constructs; effort expectancy and performance expectancy.

The role that effort expectancy plays in technology adoption has roots in Davis's seminal work with the Technology Acceptance Model (TAM) and more specifically his investigation into perceived ease of use (Davis F. , 1986). Perceived ease of use is very similar to the concept of task-fit. Task-fit focuses on the degree to which the characteristics of the technology meet the requirements needed to complete the task. Goodhue and Thompson posit the importance of task-technology fit in explaining how an individual's performance may be impacted by the alignment of the task characteristics and the characteristics of the technology (Goodhue & Thompson, 1995). This is a vital element of technology adoption theory with overlaps to compatibility as explored by Moore and Benbasat (Moore & Benbasat, 1991) and to job relevance as detailed in the TAM 3 model (Venkatesh & Bala, 2008). Effort expectancy as an explicit construct was detailed in the UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003). In this model, effort expectancy explains the ease of use of the system as perceived by the individual interacting with the system. Within the LA adoption framework, effort expectancy is defined as the ease of using LA tools and technology as perceived by the higher education faculty member.

Performance Expectancy is the degree to which the higher education faculty member believes that using LA will help them to better achieve their pedagogical goals. Behavioral intention and action are often based on a value proposition. In the original TAM model, the value proposition states intention to use is predicated on the value of ease of use and perceived usefulness (Davis F. , 1986). What is implied here is the user sees value in adopting a system because the system will not only prove to be useful, but the system is also easy to use and thus does not impart a high cognitive load. The value proposition is further explored in the foundational UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003). Here the researchers specifically incorporate performance expectancy into the research model and define the construct as the degree to which the user believes using the system will help them to perform their job. As it pertains to LA, higher education faculty will likely need to see a value proposition for adoption. Performance expectancy speaks directly to this interpreted value proposition.

Content knowledge from TPACK correlates to the knowledge that a faculty member has on their profession and content domain. In essence, content knowledge embodies what it means to a professional educator within a specific area of expertise. I.e., one's professional identity. The multi-faceted nature of professional identity results in difficulty establishing a strict definition (Trede, Macklin, & Bridges, 2012). But the research does purport elements of attitude, beliefs and standards that are consistent with one's primary area of profession. Professional identity is an important area of study (Barbour & Lammers, 2015) and certainly within education (Day, Kington, Stobart, & Sammons, 2006; Barbara-i-Molinero, Cascon-Pereira, & Hernandez-Lara, 2017; Trede, Macklin, & Bridges, 2012; Haamer, Lepp, & Reva, 2012). However, professional identity has not been an area of study within traditional technology adoption research. Trede et al., (Trede, Macklin, & Bridges, 2012) specifically point to the importance of professional identity and how professional identity shapes practice, *"All point towards the notion that professional identity is a way of being and a lens to evaluate, learn and make sense of practice."* If professional identity is truly a lens for how one approaches their professional practice, there is a strong possibility that it plays an important role in adopting technologies. Teachers tend to have a very strong professional identity as teaching can tend to be more of something you are versus something you do (Korthgen, 2004).

Incorporating learnings analytics into day-to-day professional practice is a complex undertaking. HEIs may or may not be well positioned for such a task. Factors such leadership & stakeholder involvement, analytics culture & capabilities, and existing technologies all play a key role in determining how well a HEI is positioned to incorporate LA (Alzahrani, 2023). The strength of the HEI's LA readiness embodies the strength of these factors. A faculty member's perception of the institutional LA readiness is an important area of study as it pertains to adopting new technology.

Using TPACK as the theoretical lens, the research model depicted in Figure 2 extends traditional technical adoption models to include professional identity expectancy and perceived LA readiness. Within the model, the independent constructs are operationalized through Data Tools & Technology Efficacy, Data Cycle Literacy, Effort Expectancy, Performance Expectancy, and Professional Identity Alignment. The dependent construct is Willingness to Adopt Learning Analytics. An interaction effect is hypothesized through the impact of Perceived Institutional Learning Analytics Readiness on the relationship between Effort Expectancy and Performance Expectancy on the dependent construct.

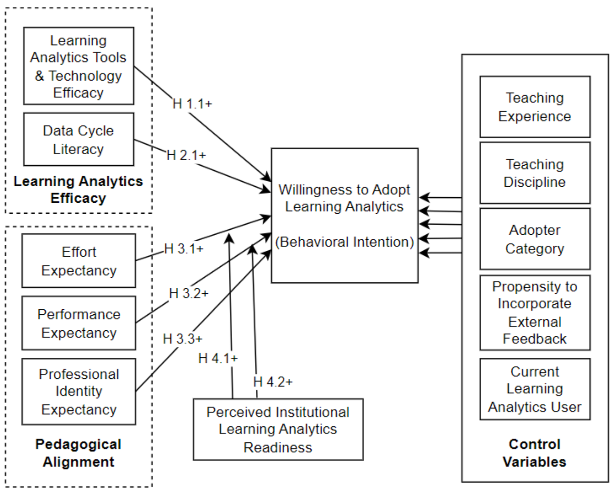

Figure 2. Research Model

The model presents the following hypotheses:

- H 1.1: The stronger a higher education faculty member perceives their efficacy with LA tools and technology, the more willing they will be to adopt LA into their professional practice.
- H 1.2: The stronger a higher education faculty member perceives their literacy with the data cycle, the more willing they will be to adopt LA into their professional practice.
- H 2.1: The higher the effort expectancy (ease of use) as perceived by the higher education faculty member, the more willing they will be to adopt LA into their professional practice.
- H 2.2: The higher the performance expectancy as perceived by the higher education faculty member, the more willing they will be to adopt LA into their professional practice.
- H 3.1: The higher the professional identity expectancy as perceived by the higher education faculty member, the more willing they will be to adopt LA into their professional practice.
- H 4.1: Perceived institutional LA readiness will moderate the relationship between effort expectancy and willingness to adopt. The moderated relationship is hypothesized to strengthen the relationship such that the higher the perceived institutional LA readiness, the stronger the effect will be on willingness to adopt.
- H 4.2: Perceived institutional LA readiness will moderate the relationship between performance expectancy and willingness to adopt. The moderated relationship is hypothesized to strengthen the relationship such that the higher the perceived institutional LA readiness, the stronger the effect will be on willingness to adopt.

METHODOLOGY AND SURVEY INSTRUMENT

The main subject of study is the higher education faculty member. As compared to elementary and secondary schools, LA are emerging on a greater scale within HEIs. The Signals program at Purdue University is one such example (Arnold & Pistilli, 2012). For the purposes of this study, HEIs institutions include any institution that awards a two-year associates or master's degree, a four-year bachelor's degree, or any doctoral degree. To be eligible for the study, the survey respondent must be a full-time faculty member at such an institution. This research focused on the adoption of LA as seen through the lens of the higher education faculty member. A pilot survey was constructed in Survey Monkey and the link to complete the survey was distributed via email to faculty at a small university located in the Midwest region of the United States. A representative at the university emailed the link via a generic faculty distribution list. As such, the principal researcher of this project was not directly involved in determining survey respondents. Additionally, by using a generic faculty distribution list, individual faculty members were not explicitly targeted. The analysis of the pilot study showed weaknesses in factor loadings and overall question design. Consultation with a psychometrician and better alignment to existing technology adoption measurement instruments informed the creation of the final survey. The final survey was also built in Survey Monkey and distribution was completed using their distribution support services. The Survey Monkey distribution mechanism can target individuals that work in the education sector, but it cannot specifically target higher education faculty. As such, a filter question was added at the beginning of the final survey. The filter question asked the respondent what their primary role was in the education industry. If a respondent selected, "Full time higher education faculty at an institution that awards 2-year, 4-year and/or doctoral degrees", they were presented with an opportunity to complete the full survey. Otherwise, the respondent was not allowed to complete the survey and the survey process terminated.

The final survey aligns to the final research model. LA efficacy is envisioned through two independent constructs; LA tools and technology efficacy (eight items using a five-point Likert scale) and data cycle literacy (four items using a five-point Likert scale). The items chosen for LA tools and technology efficacy are author created, but heavily influenced from prior work in efficacy and LA usage (Dunn, Airola, Lo, & Garrison, 2013). Prior work in data cycle theory and LA design (Clow, 2012; Greller & Drachsler, 2012; Bakharia, et al., 2016) provided a framework for the author created items of data cycle literacy.

Pedagogical alignment is comprised of the independent constructs of effort expectancy (four items using a five-point Likert scale) and performance expectancy (six items using a five-point Likert scale). The instrument used in testing the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a strong foundation for this research (Venkatesh, Morris, Davis, & Davis, 2003). The four final items used for effort expectancy in the UTAUT study were adapted with slight wording changes. The initial survey used in UTAUT included twenty-four items to measure performance expectancy. A review of the original twenty-four items revealed six that were appropriate for this study. Two of the final items used to measure performance expectancy in UTAUT were used in this study and were slightly adapted for appropriate wording changes. Additionally, four additional items were taken from the original list of items used in UTAUT.

The final independent construct is professional identity expectancy (four items using a five-point Likert scale). Previous work in institutional logics to measure professional identity (Barbour & Lammers, 2015) helped to shape the author created items to measure professional identity expectancy.

The interaction effect as influenced by perceived institutional LA readiness was measured with five items; each using a five-point Likert scale. Organizational culture and infrastructural readiness are important elements of successful business intelligence project implementation success (Hasan, Miskon, Ahmad, Syed, & Maarof, 2016; Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). This notion also holds true for HEIs and LA adoption (Alzahrani, 2023). The principal focus of study for the current LA adoption study is the higher education faculty member. It is through their lens that willingness to adopt is being investigated. Congruent to that line of thinking, institutional readiness is measured through the faculty member's perception of the institution's readiness. It is understood that perceptions will widely vary, even within the same institution. Future work could include data collection that more objectively measures an institution's data centric culture.

The dependent construct measuring the behavioral intention of willingness to adopt was modified from its original version in the pilot study of a single item to include four distinct items that sought to uncover differences between hope and intention as well as temporal differences between short- and long-term willingness to adopt. The number of control variables was also increased in order to validate a more robust model.

DATA COLLECTION AND PRELIMINARY ANALYSIS

The broad target audience for this research project was individuals who work within the educational sector and reside in the United States. Since higher education faculty could not be individually targeted, a filter question was added to the final survey. If a survey respondent indicated they were a faculty member at a HEI that awards two-year associates or master's degrees or four bachelor degrees or doctoral degrees, they were permitted to respond to the entire survey. Otherwise, the respondent bypassed the survey questions and were presented with a message indicating they did not qualify for the survey. All survey responses, regardless of full completion, were collected by Survey Monkey and made available for download in various formats. The collected surveys were initially downloaded from Survey Monkey into a CSV format that was later opened using Microsoft Excel 2016. A total of 1330 individual survey responses were collected. Of this total, 259 respondents indicated they were a higher education faculty member. These 259 responses represented the initial list for further analysis. However, of the 259, 37 surveys were not fully completed. These 37 were removed from future analysis leaving a total of 222 respondents. The 222 completed surveys were used in all future analysis.

The initial preprocessing of the data occurred in Microsoft Excel 2016. After the total number of surveys was filtered down to the final 222, unique names were created for each individual data element. For example, DTT_01, DTT_02, DTT_03, ..., DTT_08 were given to the eight items used to measure learning analysis tools and technology construct. EE_01, ... EE_04 were assigned to the four items used to measure effort expectancy. This process was repeated for all items used to the measure the independent and dependent constructs as well as the control variables and other demographic data collected by default in Survey Monkey. Where appropriate, numeric data was recoded as nominal data. For example, the control variable of technology adopter category was recorded in Survey Monkey as a numerical response. Utilizing VLOOKUP, the numerical response was translated into a nominal response like "Late Majority". A similar process was completed for questions like teaching discipline. If a nominal response was left unanswered by the survey respondent, #N/A was coded. Microsoft Excel was not used to aggregate any of the responses by construct. That analysis was completed in JMP. The final surveys with recoded responses were saved and then later imported into JMP Pro 15.0 for complete analysis.

Exploratory factor analysis (EFA) was performed as a preliminary step to assessing construct reliability and validity. A maximum likelihood with Varimax rotation was used when performing the factor analysis. EFA was performed with 7 identified factors in an effort to match the number of factors in the theoretical model (see Table 1). Opinions seem to differ on minimum viable factor loadings. A quick Google search will find minimum thresholds as low as 0.3 with other recommended values of 0.4, 0.6 or even 0.7. Using a rule of thumb that states a CFA loading of 0.5 or greater reflects the items extract sufficient variance from the respective variable (Hair, Black, Babin, & Anderson, 2015), the data supports strong communal loadings within the constructs and relative strength of differentiation between constructs. The items measuring LA tools and technology efficacy (DTT items) load very strongly together (all loads >= 0.5) and do not load well on other factors. Data cycle literacy (DCL items) exhibits very similar results. All items for LA readiness (LAR items) load higher than 0.5 and many are closer to the more stringent value of 0.7. The items load stronger as a separate factor than associated with any other factors. Effort expectancy (EE items), performance expectancy (PE items), and professional identity expectancy (PI items) did demonstrate loading on a communal factor. With the exception of one item (PE_04 factor load = 0.68), all performance expectancy loadings were 0.7 or greater. Effort expectancy loads were closer to 0.5 than 0.7, but did cluster well within a factor. All professional identity expectancy loads are 0.64 or greater which is higher the 0.5 rule of thumb and very close to the higher metric of 0.7. The dependent construct items (ITU items) loaded stronger as a separate factor, but also showed some strength loading with effort expectancy, performance expectancy, and professional identity expectancy. Overall, the factor loadings support the strength of the measurement items for the individual latent constructs in the theoretical model with an observation that effort expectancy, performance expectancy, and professional identity expectancy are closely related constructs. Future work may value from additional item analysis and an effort to untangle effort, performance, and professional identity expectancy.

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
DCL_01	0.318	0.427	0.662	0.176	0.071	0.108	0.188
DCL_02	0.264	0.450	0.664	0.255	0.114	0.078	-0.140
DCL_03	0.284	0.413	0.744	0.208	0.176	0.008	0.079
DCL_04	0.293	0.390	0.690	0.215	0.117	0.214	-0.062
DTT_01	0.221	0.715	0.080	0.118	0.097	0.062	0.237
DTT_02	0.202	0.784	0.124	0.143	0.128	0.083	-0.084
DTT_03	0.205	0.795	0.198	0.092	0.170	0.128	0.096
DTT_04	0.150	0.719	0.250	0.209	0.142	-0.003	0.085
DTT_05	0.209	0.773	0.188	0.113	0.139	0.077	0.008
DTT_06	0.228	0.754	0.115	0.041	0.079	0.157	-0.072
DTT_07	0.181	0.699	0.361	0.143	0.027	0.105	-0.063
DTT_08	0.219	0.779	0.203	0.228	0.069	-0.022	-0.071
EE_01	0.463	0.406	0.348	0.310	0.096	0.322	0.135
EE_02	0.457	0.287	0.179	0.204	0.207	0.542	0.027
EE_03	0.498	0.259	0.295	0.219	0.174	0.472	-0.057
EE_04	0.436	0.243	0.346	0.220	0.321	0.216	0.045
ITU_01	0.527	0.239	0.184	0.219	0.472	0.156	0.145
ITU_02	0.467	0.299	0.255	0.222	0.413	0.112	-0.028
ITU_03	0.434	0.220	0.080	0.216	0.585	0.070	-0.081
ITU_04	0.460	0.209	0.140	0.154	0.635	0.083	0.057
LAR_01	0.502	0.196	0.094	0.479	0.127	0.153	0.267
LAR_02	0.333	0.224	0.175	0.524	0.072	0.301	0.212
LAR_03	0.343	0.251	0.081	0.618	0.147	0.152	-0.152
LAR_04	0.305	0.205	0.269	0.678	0.223	-0.003	-0.060
LAR_05	0.347	0.145	0.238	0.699	0.109	0.031	0.058
PE_01	0.709	0.224	0.211	0.151	0.054	0.158	0.253
PE_02	0.720	0.286	0.112	0.223	0.157	0.185	0.050
PE_03	0.723	0.178	0.110	0.174	0.193	0.161	-0.090
PE_04	0.683	0.190	0.141	0.209	0.130	0.276	0.133
PE_05	0.704	0.131	0.220	0.183	0.209	0.040	0.130
PE_06	0.773	0.270	0.125	0.189	0.178	0.106	-0.004
PI_01	0.634	0.191	0.238	0.292	0.038	-0.144	0.008
PI_02	0.710	0.205	0.122	0.228	0.225	0.071	-0.238
PI_03	0.668	0.231	0.268	0.162	0.181	0.012	-0.052
PI_04	0.656	0.280	0.208	0.274	0.158	0.053	-0.084

Table 1. EFA Factor Loadings

Constructs were assessed for reliability and validity. As a first step, construct reliability was calculated using Microsoft Excel 2016. See Table 2. A reliability metric of 0.7 or greater tends to indicate solid reliability (Hair, Black, Babin, & Anderson, 2015). However, it is possible that construct reliability may calculate lower and still represent good reliability when compared to multiple other goodness of fit metrics (Hair, Black, Babin, & Anderson, 2015). As can be seen, most all constructs have a reliability score greater than 0.7. Effort expectancy presents the lowest value at 0.52 and the dependent construct of willingness to adopt learning analytics has a reliability measurement of 0.61. Loading values less than 0.5 will propagate to construct reliability scores that fall short of ideal targets. While these two reliability scores are slightly less than 0.7, they remain in the model for future analysis.

Construct	Construct Reliability
Learning Analytics Tools and Technology Efficacy	0.91
Data Cycle Literacy	0.78
Effort Expectancy	0.52
Performance Expectancy	0.87
Professional Identity Expectancy	0.76
Percieved Learning Analytics Readiness	0.74
Wilingness to Adopt Learning Analytics	0.61

Table 2. Construct Reliability Values

Construct validity can be examined multiple components with average variance extracted (AVE) being one of the most common. (Hair, Black, Babin, & Anderson, 2015). AVE was manually calculated using Microsoft Excel 2016. See Table 3. Using a rule of thumb of 0.5 or greater to indicate acceptable convergence, some constructs show high convergence and others are weaker. Learning analytics tools and technology efficacy, data cycle literacy, performance expectancy, and professional identity expectancy all show adequate convergence. Effort expectancy, perceived learning analytics readiness, and willingness to adopt learning analytics do fall short of the desired threshold. It should be noted that perceived learning analytics readiness is theorized to have a moderating effect on the effect of effort and performance expectancy and not a direct effect on willingness to adopt. The relatively low AVE for willingness to adopt learning analytics may indicate that effectively measuring behavioral intention is a challenging undertaking.

Construct	AVE
Learning Analytics Tools and Technology Efficacy	0.57
Data Cycle Literacy	0.48
Effort Expectancy	0.22
Performance Expectancy	0.52
Professional Identity Expectancy	0.45
Percieved Learning Analytics Readiness	0.37
Wilingness to Adopt Learning Analytics	0.28

Table 3. Average Variance Extracted (AVE) Values

Correlation analysis between constructs is used as a preliminary technique to access the strength of each of the hypotheses. Table 4 provides a summary of the correlations between each of the constructs. Effort expectancy, performance expectancy, and professional identity expectancy show these highest correlations. These metrics provide early support for hypotheses 2.1, 2.2, and 3.1. Learning analytics tools and technology and data cycle literacy show the weakest correlations. These metrics do not provide strong support for hypotheses 1.1 and 1.2.

	DTT_TOT	DCL_TOT	EE_TOT	PE_TOT	PI_TOT	LAR_TOT	ITU_TOT
DTT_TOT	1.00						
DCL_TOT	0.71	1.00					
EE_TOT	0.63	0.72	1.00				
PE_TOT	0.54	0.61	0.79	1.00			
PI_TOT	0.55	0.64	0.72	0.85	1.00		
LAR_TOT	0.53	0.62	0.71	0.70	0.70	1.00	
ITU_TOT	0.55	0.60	0.72	0.76	0.73	0.65	1.00

Table 4. Correlation Matrix for Constructs

Using JMP Pro 15.0, a multiple linear regression model was run using DTT_TOT, DCL_TOT, EE_TOT, PE_TOT, and PI_TOT as the independent variables and ITU_TOT as the single independent variable. Table 5 shows the estimates for the coefficients. The linear regression model supports the correlations in that learning analytics tools and technology and data cycle literacy are likely not predictors for willingness to adopt. However, effort expectancy, performance expectancy, and professional identity expectancy show strength for predicting willingness to adopt.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	2.567	0.552	4.65	<.0001*
DTT_TOT	0.029	0.019	1.53	0.1278
DCL_TOT	0.021	0.036	0.58	0.5629
EE_TOT	0.165	0.059	2.78	0.006*
PE_TOT	0.164	0.045	3.67	0.0003*
PI_TOT	0.167	0.061	2.74	0.0067*

Table 5. Linear Regression Model Parameters

Figure 3 is a visualization to help evaluate the strength of the interaction effect of perceived learning analytics readiness on the relationship between effort expectancy and willingness to adopt. The figures depict effort expectancy along the x-axis and willingness to adopt learning analytics along the y-axis. Additionally, the graph is partitioned by binning the total perceived learning analytics readiness scores. The graphs provide early support for the notion that willingness to adopt scores will be higher for individuals that show relatively equal effort expectancy scores, but demonstrate a higher perceived learning analytics readiness score.

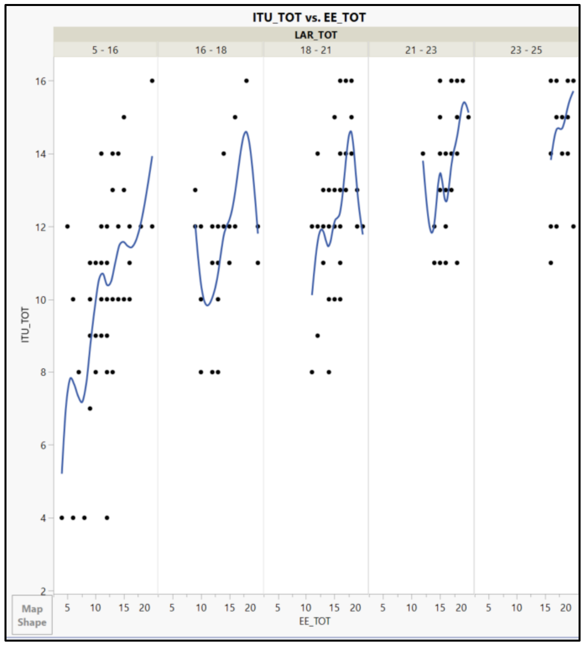

Figure 3. Influence of LAR on EE and ITU

In a similar fashion, Figure 4 helps to evaluate the strength of the interaction effect of perceived learning analytics readiness on the relationship between performance expectancy and willingness to adopt. Here again, the data provides early support for the notion that perceived learning analytics readiness increases the willingness to adopt behavior within individuals of similar performance expectancy scores.

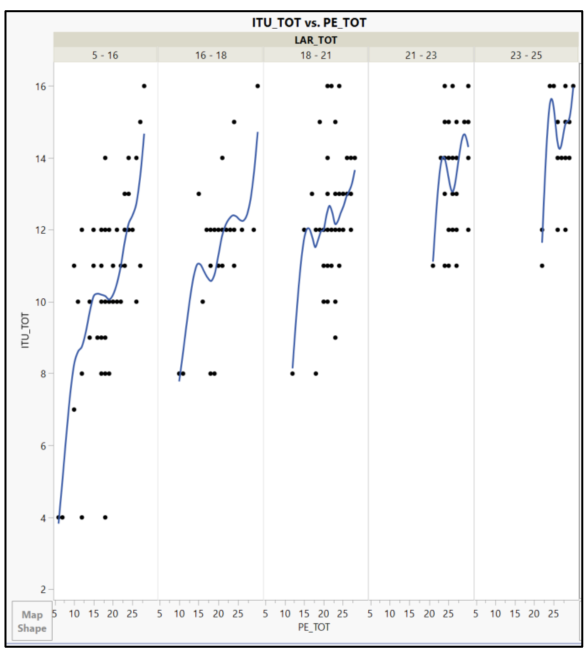

Figure 4. Influence of LAR on PE and ITU

Taken in totality, the early analysis of the data provides support for the following conclusions:

H 1.1 (not supported; poor correlation and insignificant regression estimate) – The results of the analysis do not support the hypotheses of a positive relationship between the strength of LA tools and technology and willingness to adopt LA.

H 1.2 (not supported; poor correlation and insignificant regression estimate) – The results of the analysis do not support the hypotheses of a positive relationship between the strength of data cycle literacy and willingness to adopt LA.

H 2.1 (supported; strong correlation and significant regression estimate) – The stronger the effort expectancy, the stronger the willingness to adopt LA.

H 2.2 (supported; strong correlation and significant regression estimate) – The stronger the performance expectancy, the stronger the willingness to adopt LA.

H 3.1 (supported; strong correlation and significant regression estimate) – The stronger the professional identify alignment, the stronger the willingness to adopt LA.

H 4.1 (supported; strong differentiation between LAR bins) – The strength of the perceived LA readiness had a positive effect on the dependency relationship between effort expectancy and willingness to adopt LA.

H 4.2 (supported; strong differentiation between LAR bins) – The strength of the perceived LA readiness had a positive effect on the dependency relationship between performance expectancy and willingness to adopt LA.

IMPLICATIONS AND FUTURE RESEARCH

The model gives credence to the importance of effort expectancy, performance expectancy, and professional identity expectancy on willingness to adopt. As such, research and development into LA would be well served to ensure the tools are deemed to be easy to use, have high value and alignment to existing pedagogical practices, and fully embrace the alignment to professional identity. The data also supports close linkage between effort expectancy, performance expectancy, and professional identity expectancy. Future research could explore these linkages in more detail and even seek out how to disentangle them. Additional analysis using Structural Equation Modeling (SEM) will help to provide better statistical evidence to support or refute the proposed hypotheses.

The model does show some weaknesses in places. Future research could help to determine if design gaps exist with the role that efficacy plays in adoption. Additionally, there is value in continued work with the interaction role of perceived institutional LA readiness on willingness to adopt LA.

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PRODUCER PRICE CHANGES IN SELECT U.S. INDUSTRIES AND THE CORONAVIRUS DISEASE 2019 (COVID-19)

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ABSTRACT

This paper uses the OLS with robust standard errors estimation method to regress the aggregate PPI of all commodities and 11 other sectors from different industries to measure the impact of monetary policy, the level of economic activity, the crude oil prices, and the tightness of the labor market on the producer prices using monthly data for the 2006-2023 period. The regression results are based on the stationary first difference of the variables except for a dummy variable equal to one for the years of the COVID-19 pandemic and zero otherwise.

The overall conclusions are that the PPI of industries studied has been affected by the explanatory variables in different ways and some commonalities during the years before the pandemic and those including the pandemic. Contrary to some studies that ignore the impact of monetary policy changes, the real money stock affects industries' PPI differently and cannot be ignored when studying the impact of the pandemic on the PPI. The Fed needs to have a more disaggregated and granular approach to the conduct of monetary policy during economic and social shocks. The crude oil prices, along with the economic activity, affect most industries studied. The tightness of the labor markets as a way of higher wages to raise producer prices is not as significant as suggested by some of the studies cited in this paper. It may also be suggested that the fiscal policy needs to be more targeted during economic shocks and pandemics, mainly when financed by quantitative easing of the Fed. This study focused on only a handful of sectors. With additional resources, one should study the impact of the suggested economic variables on prices for all sectors and industries.

INTRODUCTION

On March 11, 2020, the World Health Organization characterized COVID-19 as a pandemic (WHO, 2020; CDC, 2023). However, the first American with COVID-19 infection was announced On January 21, 2020. Shortly after the pandemic outbreak, the U.S. instituted shutdowns and social distancing, and Americans were under a stay-at-home or shelter order. Billions of people were under quarantine and without jobs. The U.S. unemployment rate reached 14.7%, and the equity market, as indicated by major indexes, the Dow Jones Industrial Average and the S&P 500, lost their value by 37 and 34 percent, respectively (History.Com Editors, 2023). Carlsson-Szlezak et al. (2020) provided a brief comment to shed light on understanding the economic shock of COVID-19. They argued that the global social distancing and shutdowns would result in a worldwide recession unchartered previously. They questioned the path of shock and recovery and whether the world economy could return to its pre-pandemic state without any permanent structural costs. The authors consider three recession-recovery paths following the 2008 financial crisis in Canada (V-shape), the U.S. (U-shape), and Greece (L-shape). They concluded that in the U.S., besides the $2 trillion stimulus package, there was a need for innovation (a medical breakthrough) to prevent a U-shape discovery and attain a more closely V-shape recovery path. The U.S. downgraded its national emergency on May 11, 2023, when the pandemic had already taken seven million lives globally, including 1.1 million in the U.S.

The monthly Personal Consumption Expenditures (Chain-Type-Price Index, in 2017 prices; CPE) measured as percentage change from a year ago, reached its lowest level of 0.4 percent in April 2020 before rising to its highest level of 7.1 percent since the pandemic in June 2022. The CPE Index declined steadily to 2.6 percent in November 2023. The Consumer Price Index for all urban consumers (CPI) closely traced the CPE Index, reaching its minimum at 0.2 percent in May 2020, rising to a maximum of 8.9 percent in April 2022, before declining to 3.1 percent in November 2023. The monthly percentage change of the Producer Price Index for all commodities from a year ago took a different path than the CPEI and the CPI. The monthly percentage change in PPI remained negative from May 2019 to November 2020 at -0.7 and -0.4 percent, respectively, reaching the highest decline of 8.2 percent in April 2020. During December 2021- December 2023, the monthly percentage change in the PPI was positive and reached its highest at 22.4 percent in June 2022. The PPI indicates a continuous monthly disinflation of 9.4 percent in June 2023 and declined to 3.2 percent disinflation in December 2023 (Federal Reserve Economic Data; FRED, 2024).

This study investigates the impact of COVID-19 and other monetary and non-monetary economic variables on select industries' producer price index (inflation and disinflation). Many researchers have studied consumer inflation since the pandemic of 2029 (Bernanke et al., 2023; Konczal, 2023; Almuzara et al., 2023; Almuzara & Sbordone, 2022;

Harding et al., 2023; Ball et al., 2022; Xu & Lien, 2022; Oduntan & Ajayi, 2023; Shapiro, 2020). However, less attention has been given to producer price changes since the pandemic. This study contributes to the literature by studying producer price changes by considering the pandemic in 2019. The following section provides a select but thorough review of the post-COVID-19 economic literature, followed by a presentation of the empirical model and the data used. The regression results are discussed next, followed by the conclusions.

A POST-COVID-19 (SELECT) REVIEW OF LITERATURE

Economic research and debate started almost immediately after the onset of COVID-19. The macroeconomic impact of the pandemic on economic growth, employment, aggregate demand, aggregate supply, the labor market, and inflation was studied, and some authors looked for parallels and analogies with other crises, such as the financial crisis of 2007-2008 (Coibion et al., 2020). This section presents a select and non-exhaustive review of recent literature on the macroeconomic impact of COVID-19.

Coibion et al. (2020) used a wave of surveys of 10,000 respondents to study the macroeconomic costs of COVID-19 on employment status (the labor market), consumer spending, liquidity, and portfolio allocations, as well as macroeconomic expectations of inflation, employment, and mortgage rates. They reported pessimistic household expectations of employment (higher unemployment in three to five years) and aggregate spending cuts by 31 log percentage points. They also expected lower mortgage rates, increased uncertainty, and a lower future inflation rate. The respondents also reported moving out of foreign equity markets and seeking more liquid savings vehicles domestically. Sanchez (2021) studied the global impact of COVID-19 in 171 countries. The countries are separated into three low, medium, and high-income groups. The study highlights the global differences in the effects of the pandemic on economic growth and fiscal and monetary responses by comparing the economic forecasts of the International Monetary Fund (IMF) made in 2019 with the actual values for 2020. The author finds a significant impact of COVID-19 on the gross domestic product (GDP) of all countries in the study, with a more noticeable decline in the GDP of middle-income countries and a less severe decline in the poorest countries because of ineffective lockdowns and in the rich countries because of more effective fiscal and monetary responses. World Economic Report (2022) categorizes COVID-19 as causing the most significant global economic crisis since the Depression of the 1930s. The report mentions the success of immediate responses to the pandemic in saving lives. The fiscal response as a percentage of GDP was large in high-income countries and very low in low-income nations. The middle-income countries' responses varied among them substantially. However, this comes with considerable public and private debt rises and a dramatic rise in global poverty and inequality.

The effect of vaccinations on economic activities has been a focus of many studies in the U.S. and other countries. Cevik (2023) used panel data from January 1, 2020, to October 2, 2022 from three Baltic countries (Estonia, Latvia, and Lithuania) and estimated a log model of regressing aggregate and 33 different categories of consumer spending based on debit and credit card transactions on the number of COVID-19 vaccinations, the number of new COVID-19 cases, the stringency index, the containment and health index (a vector of health policy measures), and the economic support index (government response measures). The study concludes that 1- the vaccination and other policy measures softened the severe impact of the pandemic and supported consumer spending; 2- the services sectors(contact-intensive) benefited more from immunization compared to the goods sectors; 3- a granular estimation of 33 consumption spending categories indicates that the impact of vaccination is more significant in sectors directly regulated by lockdowns. Hansen and Mano (2021) quantified the effect of vaccinations on the U.S. economy for the period end-2020 to mid-2021 using weekly county-level data. They concluded that the vaccination elasticity for unemployment and weekly consumer spending was 0.004 and 0.6 percent, respectively.

The pandemic caused uncertainty, and its impact on economic activity has been the focus of other research. The argument is that COVID-19 elevated economic uncertainty, resulting in higher unemployment, lower inflation, and lower interest rates. Liu and Leduc (2020) use the Chicago Board Options Exchange Volatility Index (VIX) to measure uncertainty. They refer to the 2007-2008 financial crisis, the 2018 U.S. trade negotiations with China, and the Covid-19 pandemic when the VIX jumped substantially. They used the changes in VIX, which are at least 1.65 times the average value of VIX, as an exogenous shock to measure the impact of uncertainty on the unemployment rate, the inflation rate, and the three-month Treasury yield employing data from January 1986 to January 2020. The study focused on the immediate impact of uncertainty and excluded other factors from their research, such as the supply chain, labor market tightness, and lockdowns. They concluded that uncertainty would increase unemployment by one percent, reduce inflation by two percent, and cut the interest rates to zero.

The inflation rate in the U.S., measured by the percentage change in monthly CPI from the previous year, was 0.2 percent in April 2020 and rose to its highest since the pandemic at 8.9 percent in June 2022. The rate has declined steadily to 3.1 percent in January 2024. Shapiro (2020) monitored the impact of the pandemic on core personal consumption expenditures (PCE) inflation by decomposing the inflation into two mutually exclusive groups of 124 categories of PCE inflation. The groups consist of COVID-19-sensitive and COVID-insensitive items. The COVID-sensitive category includes any item with a positive or negative price or quantity change over its average of 10 years before a change from February to April 2020. He further separates the demand and supply factors contributing to the PCE inflation in the COVID-sensitive category by designating a significant difference between a price and quantity changing the same direction from their 10-year preceding average as demand factor and changes in price and quantity in opposite directions as supply factors. He observed that 18% of the COVID-19-sensitive categories are demand-affected, 8% are supply-affected, and the remaining 75% are ambiguous. He concluded that at the onset of the pandemic in 2020, declines in consumer spending on goods and services offset the supply constraints and led to a drop in the CPE inflation in COVID-19-sensitive categories.

The dynamics of inflation in the U.S. have renewed researchers' interest in the coming back of the Philips curve (Barnichon et al., 2021; Ball et al., 2022; Harding et al., 2023). Barnichon et al. 2021 estimated a standard Philips curve model by regressing the core PCE inflation on the one-quarter lagged vacancy-to-unemployment ratio (v/u) while controlling for expectations of future inflation for the period 1960-2021. They also estimated the impact of the American Recovery Plan (ARP) of 2021 on the v/u ratio to assess the effects of unprecedented fiscal expansion on inflation via the tightness of the labor markets as measured by the v/u ratio. They concluded that the ARP caused a transitory rise in the v/u ratio, resulting in 0.3 percentage point higher inflation per year through 2020. Their conclusions are based on the constancy of business expectations about the future inflation rate. Ball et al. (2022) decompose the U.S. inflation since 2020 into core inflation and the deviations of headline inflation from the core. Their estimation results indicate that the vacancy-to-unemployment ratio and past shocks to the headline inflation explain the rise in the core inflation. Rises in energy prices and supply chain challenges explain the headline shocks. The simulation results of their study under different assumptions about the future unemployment rate project that under the Federal Reserve (the Fed) System's' projection of a 4.4% unemployment, the inflation returns to a path close to the 2% target of the Fed only under benign assumptions about inflation expectations and the Beveridge curve. Harding et al. (2023) propose a non-linear Philips curve stemming from a quasi-kinked demand. They stipulate that their model has significant policy implications for the monetary authorities because they face a more severe trade-off between inflation and economic activity. The cost-push inflationary pressures overwhelmed the expansionary impact of monetary policy.

Bernanke et al. (2023) investigate the causes of the U.S. inflation after the pandemic. They employ a four-equation structural vector autoregression (SVAR) model using quarterly data for the first quarter of 1990 to the fourth quarter of 2019 and estimate a wage, a price, a short-run, and a long-run equation. They include the pandemic period (2020Q1-2023Q1) for the price equation to capture the effects of variation in the sectoral shortages on the prices. The exogenous and control variables in different equations of their model include expected wages, tightness of the labor market measured by the v/u ratio, commodity price shocks, supply-chain difficulties, and the productivity trend. They conclude that the inflation in 2021 was caused by price shocks, such as sharp increases in commodity prices and sectoral price increases because of the higher aggregate demand and supply constraints on different sectors. This study does not consider any possible impact of significant monetary expansion (quantitative easing of the Fed) on price and wage inflation.

Other studies similar to Bernanke et al. (Aharon et al., 2023; Oduntan et al., 2023; Barnichon et al., 2021; Harding et al., 2023) do not investigate the monetary aspects of inflation as postulated by Milton Friedman and other monetarists. Hanke and Greenwood (2024) consider the quantity theory of money and argue that changes in the inflation rates have been caused by historically unprecedented and sustained expansion of money supply (M2) at the onset of COVID-19 in 2020, reaching an annual increase of 26.9 percent in February 2021. Their message to the Fed is simply that *"…The Fed must realize that monetary policy is not about interest rates, but about the rate of growth in the money supply*" (Hanke & Greenwood, 2024, p. 1). They further postulate that the 35 percent increase in M2 between March 2020 and March 2023 caused a 10 percent real economic growth, 9 percent was held in the form of additional money demand, and the remaining 16 percent of the M2 growth contributed to the headline CPI inflation. The authors are critical of those studies that look into non-monetary causes of inflation, such as the tightness of the labor market, and omit the impact of significant monetary expansion during the COVID-19 pandemic. Lien & Xu (2022) study the impact of COVID-19 on price co-movements in China and include monetary policy measures such as changes in the required reserves by the Central Bank of China and discount window activities. Commodity prices (gold, crude oil, and Bitcoin), financial markets activities (indicators for consumer spending), and the exchange rate between the U.S. dollar and Yuan are control variables used in their regression model. However, the monetary factors are part of a principal components model, and their direct impact is not modeled.

The studies cited above emphasize consumer inflation by using CPI or PCE to measure inflation. Since the pandemic, inflation measured by the CPI and the producer price index for personal consumption (PPI) have differed in different periods. Inflation measured by the PPI has received little or no attention in post-pandemic studies of the causes and dynamics of inflation. This paper addresses some of these issues using the PPI to measure inflation.

THE MODEL AND THE METHODOLOGY

This paper contributes to the fast-growing economic studies of inflation since the COVID-19 pandemic in a few ways. First, it regresses the PPI as a whole and about select industries (health care, hospitality, and manufacturing) on a set of explanatory (control) variables and a dummy variable for the COVID-19 period. Shapiro (2020) monitored the effects of COVID-19 on 124 categories of personal consumption expenditure index grouped into COVID-19-sensitive and insensitive items. COVID-19-sensitive items have significant price or quantity changes between February and April 2020 compared to the average change over the preceding ten years. He concluded that the service categories, such as air travel and hotels, were very sensitive to COVID-19 and experienced extraordinary price and quantity declines.

Second, unlike the abovementioned inflation studies, this paper uses the PPI instead of the CPI or the PCE to measure inflation. According to the U.S. Bureau of Labor Statistics, there are many conceptual and definitional differences between them. The scope, categorization, and technical measurement differences result in different inflation rates measured by the CPI and PPI. For example, the CPI includes the price of imports, but the PPI excludes it. In addition, the CPI includes medical services directly paid for by consumers; however, the PPI includes medical services paid for by third parties and the government. The PPI and the CPI treat services containing interest rate charges differently. The CPI does not include the interest rate component of the price of services, but the PPI includes those interest expenses. Interestingly, the PPI does not include the costs of transporting and retailing goods in the cost of goods itself; therefore, the retailing markups are absent from the PPI.

Third, the impact of the significant monetary expansion measured by M2 (Hanke & Greenwood, 2024) and the tightness of the labor markets measured by the vacancy-to-unemployment ratio (Bernanke et al., 2023) since COVID-19 are explicitly modeled in this paper. Fourth, a dummy independent variable is used to measure the direct impact of COVID-19 on the prices measured by the PPI for the period 2006-2023. Similar to some abovementioned studies, this paper divides the regression into pre-COVID-19 (2006-2018) and the entire period (2006-2023), including the post-COVID-19 period. The V/U series was discontinued in 2018 and is excluded from the model with the COVID-19 dummy. However, a quadric time trend OLS model is used to extrapolate the trend values of the V/U for the period beyond 2018. This paper uses a dummy variable equal to one for the duration of the pandemic and equal to zero for the period before the pandemic.

This paper uses the ordinary least squares (OLS) with robust standard errors to estimate concurrent and lagged versions of the model presented below.

$$P_t = a_0 + a_1\,\Delta M_2 + a_2\,\Delta EA + a_3\,\Delta COP + a_4\,D + a_5\,V/U + e_t \tag{1}$$

Where:

P_t = The producer price Index for select industries at time t,
M_2 = The Real Money Stock,
EA = The economic activity index,
COP = The crude oil price,
D is a Dummy variable = 1 during the pandemic, equal to zero otherwise, and
V/U = Vacancy to Unemployment Ratio (available up to 2018)
e_t = The error.

The coefficients $a_1, a_2, a_3,$ and a_5 are theoretically expected to be positive. The sign of the dummy coefficient is empirically estimated.

Gagliardone and Gertler (2023) studied the monetary policy origins of inflation. They use a structural Vector autoregressive model and demonstrate the impact of oil price shocks and easy monetary expansion on unemployment and inflation since 2010. They conclude that the Fed contributed to a substantial rise in aggregate demand and subsequent inflation. This paper explicitly considers the effect of monetary expansion and crude oil prices on the PPI. A measure of real economic activity is included in the model to proxy the impact of supply disruptions and supply-chain difficulties. On a global scale, it is suggested to use a measure of global economic activity and its role in global macroeconomic performance (Nonejed, 2020; Kilian, 2019). This research uses the coincident economic activity index for the U.S. as a measure of economic activity to capture the combined impact of the aggregate demand and aggregate supply changes on the PPI.

The PPI used as the dependent variable in this study includes the PPI for all commodities (AC), industrial commodities (IC), total mining Industries (TMI), air transportation (AT), new car dealers (NCD), aircraft manufacturing (AM), medical equipment and supplies manufacturing (MESM), Pharmaceutical and medicine manufacturing (PMM), general medical and surgical hospital (GMSH), office of physicians except mental health (OPH), hotels and motels except casino hotels industries (HM), and scheduled passenger air transportation (SPAT). The spot crude oil price-West Texas Intermediate (WTI), is used for the oil variable. All data are from the St. Louis Fed's Federal Reserve Economic Data (FRED). The level of macroeconomic variables is expected to have unit roots and be nonstationary. The Augmented Dickey-Fuller test of stationarity (ADF) is used to identify the variables that need to be the difference or log-differenced in the regression model. Monthly data from January 1st, 2006, to April 4th, 2023, are used for the estimation.

EMPIRICAL RESULTS

The ADF tests indicate that all variables in the model are nonstationary at their level, but their first difference is stationary. The OLS robust standard errors method is used to regress the first difference of the PPI of select industries on the first difference of the explanatory variable except for the dummy variable, which is measured as one or zero. Table 1 presents the best concurrent and/or lagged estimation results for 2006-2023 with the dummy variable and no V/U. The estimation results indicate that changes in M2 have a significant positive impact on the NCD's PPI. However, the PPI of the MESM (concurrently), OPH concurrently or 4-month lag), and HM with a 6-month lag move significantly against the movements of the M2. Overall, four of the 12 industries included in this study are significantly affected by monetary expansion.

The level of economic activities, measured by the coincidence economic activity index, affects the PPIs of 10 (AC, IC, AT, NCD, MESM, PMM, GMSH, OPH, HM, and SPAT) out of 12 industries studied. The PPI of GMSH moves counter-cyclically to the changes in EA. The PPI of seven industries (AC, IC, TMI, AT, NCD, PMM, and SPAT are positively and significantly impacted by the crude oil price. COVID-19, as explicitly measured by a dummy variable, has significantly contributed to higher PPIs in the AC, IC, AM, MESM, GMSH, and HM industries. Overall, the level of economic activity outranked the crude oil price, COVID-19, and the M2 in contributing to changes in the PPIs of the industries in the order listed.

Table 2 presents the results for the entire period of 2006-2023. The dummy variable is dropped in this model, and the impact of the tightness of the labor market as measured by the ratio of vacancies to the unemployment rate (V/U) is included. The monetary policy has significantly impacted the PPIs of eight industries out of 12 studied, with generally a 6-month lag. The AC, IC, and NCD PPIs move with the M2, but the PPIs of AM, MESM, GMSH, and HM move against the movements of the M2 with a lag of six months. This is the most persuading evidence that the impact of the monetary policy on producer prices cannot be dismissed.

The PPIs of the AC, IC, AT, NCD, PMM, and SPAT moved significantly with the level of economic activity and the crude oil price during the entire period of 2006-2023. The AM, GMSH, and HM PPIs moved against the economic activity with a 6-month lag. The AM and HM PPIs moved with the crude oil price with a 6-month lag, but the total mining industry's PPI moved with the COP concurrently. The tightness of the labor market contributed to higher producer prices in the MESM, GMSH, and SPAT industries. Overall, Money supply, economic activity, and crude oil price outranked the tightness of the labor market in contributing to higher producer prices. Again, the impact of monetary policy on the PPIs of eight out of 12 industries studied cannot be dismissed, and the Fed needs to consider the impact of its policies on an aggregated and more granular basis.

Table 3 presents the best results of various concurrent and lagged estimations for 2006-2018 before COVID-19. The model excludes the dummy and includes the V/U variable. For the period before COVID-19, the PPIs of two industries (OPH and SPAT) significantly moved with the monetary expansion. Five industries' PPI (AC, IC, NCD, AM, and HM) moved counter-cyclically with the M2. Five industries' (AC, IC, AM, OPH, and SPAT) PPI moved significantly with the level of economic activity, and two (NCD and MESM) moved against it. The crude oil price positively and significantly affected the PPIs of 10 out of 12 industries (AC, IC, TMI, AT, NCD, AM, MESM, PMM, HM, and SPAT) before COVID-19. The crude oil price affected the PPI of the AM and HM industries counter-cyclically with a lag of six months. The tightness of the labor market positively and significantly affected the PPI of AT, MESM, and PMM industries. The PPI of two industries (OPH and SPAT) moved counter to the V/U ratio. Overall, the crude oil price outranked M2 and EA in the number of industries it affected. The V/U was the least impactful compared to the other explanatory variables.

Table 4 summarizes the significant explanatory variables before COVID-19 and the entire study years from 2006-2023. The aggregate measures of PPI for all commodities and Industrial commodities are significantly affected by monetary policy, the level of economic activity, and crude oil price. The tight labor market can raise wages and contribute to a higher price level. However, the results indicate this is not the case for all commodities and industrial commodities. In these cases, the monetary policy plays a more significant role than the labor market.

Within the health-related sections, the office of physicians' PPI is affected by the level of economic activity with a 3-month lag and M2 with a 6-month lag before COVID-19. Only 6-month lagged M2 affected the physician's PPI for the entire period. None of the explanatory variables significantly impacted the general medical and surgical hospital's PPI before COVID-19. This sector was counter-cyclically affected by a 6-month lag of M2 and EA. The tight labor market also affects the cost of general medical and surgical hospitals. Pharmaceutical and medicine manufacturing PPI was affected by the crude oil price and the tightness of the labor market before COVID-19. During the entire period, the level of economic activity and the crude oil price were the only significant factors for PMM's PPI. The vacancy-to-unemployment ratio significantly impacted medical equipment and surgical manufacturing before and after COVID-19, but EA and COP impacted it only before COVID-19. Monetary policy significantly impacted the entire period, but not before COVID-19.

The only variable that impacted the total mining industries was crude oil prices before and after COVID-19. Neither the monetary policy nor the state of the labor market impacted the mining industry's PPI. Aircraft manufacturing was impacted counter-cyclically by M2 and cyclically by EA before COVID-19. However, for the entire period, both M2 and EA affected it counter-cyclically with a 6-month lag. New car dealers' producer prices were affected by concurrent values of M2, EA, and COP. However, M2 and EA moved with it counter-cyclically before the pandemic and cyclically for the entire period. This observation merits further study of the pricing strategies of new car dealers. The tightness of the labor market had no impact on the PPIs in these industries.

Table 4 further compares the results in Tables 2 and 3. The PPI of AC, IC, HM, AM, and NCD moved against the changes in M2 before COVID-19. During the entire years of the study, with the COVID-19 years included, the PPI of IC, HM, OPH, GMSH, MESM, and Am with varying lags moved counter to the M2 changes. The PPI of AC, IC, SPAT, OPH, and AM moved with the economic activity before COVID-19. However, The PPI of NCD moved counter-cyclically. The ten sectors significantly affected by the crude oil prices moved with it pre and post-COVID-19, some with a 6-month lag. The tightness of the labor market moved three PPIs (AT, MESM, and PMM) with it and two PPIs (OPH, SPAT) against it before COVID-19. During the entire period, changes in V/U positively and significantly contributed to changes in the PPI of SPAT, GMSH, and MESM.

Table 5 highlights the different effects of the explanatory variables for the years before the pandemic and the years pre- and post-COVID-19 years. Table 6 presents the identical effects of each explanatory variable on the PPI of different sectors. The results indicate that the hotel and motel industry is negatively affected by M2 with a 6-month lag. Related to the HM sector, the EA affected the scheduled passenger air travel industry and the AC, regardless of COVID-19. The crude oil prices positively affected the PPI of AC, AT, SPAT, PMM, AM, and NCD regardless of the pandemic. Table 7 presents the number of times an explanatory variable has been significant concurrently or lagged in the estimated models. The crude oil prices and economic activity are the top two significant variables, each with 26 appearances. The money stock (M2) appears 19 times, surpassing the eight times that the tightness of the labor market has been significant.

CONCLUSIONS

This paper uses the OLS with robust standard errors estimation method to regress the aggregate PPI of all commodities and 11 other sectors from different industries to measure the impact of monetary policy, the level of economic activity, the crude oil prices, and the tightness of the labor market on the producer prices using monthly data for the 2006-2023 period. The regression results are based on the stationary first difference of the variables except for a dummy variable equal to one for the years of the COVID-19 pandemic and zero otherwise.

The overall conclusions are that the PPI of industries studied has been affected by the explanatory variables in different ways and some commonalities during the years before the pandemic and those including the pandemic. Contrary to some studies (Bernanke et al., 2023) that ignore the impact of monetary policy changes, the real money stock affects industries' PPI differently and cannot be ignored when studying the impact of the pandemic on the prices as also evidenced by Lien & Xu (2022) in the case of the Chinese economy. The Fed needs to have a more disaggregated and granular approach to the conduct of monetary policy during economic and social shocks. The crude oil prices, along with the economic activity, affect most industries studied. The tightness of the labor markets as a way of higher wages to raise producer prices is not as significant for some industries, contrary to what is suggested by some of the studies cited in this paper. It may also be suggested that the fiscal policy needs to be more targeted during economic shocks and pandemics, mainly when financed by quantitative easing of the Fed. This study focused on only a handful of sectors. With additional resources, one should study the impact of the suggested economic variables on prices for all sectors and industries.

Table 1. The Concurrent/Lagged Results of the OLS Estimation –Dependent Variable: The Producer Price Index for Select Industries (2006-2023)

Dependent Variable	Explanatory Variable Coefficient (t-statistic)					Other statistics		
	Constant	M2	EA Dummy	COP	COVID-19	R^2	Adj. R^2	No. of Obs.
AC	0.19 (1.17)	- 0.0004 (- 0.71)	0.27 (2.o6)**P	0.29 (10.34)***P	1.2 (1.79) *P	0.62	0.61	214
IC	0.23 (1.40)	- 0.01 (-1.16)	0.20 (1.38)	0.32 (10.29)***P	1.21 (1.65)*	0.63	0.62	214
IC	0.05 (0.32)	$0.01(L_6)$ (1.03)	0.29 (5.71)***P	0.33 (11.46)***P	$1.02(L_3)$ (1.54)	0.64	0.62	209
TMI	- 0.31 (- 0.454)	(- 0.00) (- 0.002)	- 0.03 (- 0.05)	1.35 (7.98)***P	0.98 (0.47)	0.49	0.48	214
AT	0.04 (0.09)	- 0.003 (- 0.25)	1.33 (3.70)***P	0.18 (2.12)***P	0.70 (0.49)	0.09	0.07	214
NCD	- 0.26 (-1.29)	0.01 (1.85)*	0.80 (4.36)***P	0.08 (2.95)***P	0.79 (0.76)	0.14	0.12	214
AM	0.40 (5.78)***P	- 0.001 (- 0.74)	0.01 (0.21)	- 0.01 (- 0.77)	0.28 (1.76)*	0.03	0.02	214
MESM	0.14 (6.80)***P	- 0.001 (-2.91)***P	- 0.02 (- 0.44)	0.004 (1.25))	0.15 (2.26)**P	0.08	0.06	214
MESM	0.12 (6.36)***P	- 0.001 (-3.23)***P	$0.02(L_3)$ (4.38)***P	0.004 (1.15)	0.15 (2.20)**P	0.08	0.06	211

PMM	- 0.04 (- 0.07)	- 0.004 (- 0.21)	1.93 (3.74)***P	0.26 (2.12)***P	0.92 (0.45)	0.09	0.07	214
GMSH	0.32 (7.50)***P (2.18)**P	0.001 (1.07)	0.01 (0.25)	0.01 (1.28)	0.21	0.03	0.01	214
GMSH	0.33 (7.91)***P (2.20)***P	0.001 (1.28)	- 0.03(L_6) (- 3.12)***P	0.01 (1.26)	0.21	0.03	0.01	208
OPH	1.56 (8.96)***P	- 0.01 (-1.42)*	- 0.05 (-0.45)	0.01 (0.49)	- 0.22 (- 0.55)	0.01	0.01	214
OPH	1.57 (3.91)***P	- 0.01(L_4) (-2.22)**P	0.12 (2.82)***P	0.01 (0.59)	- 0.41 (- 1.06)	0.01	0.01	211
HM	0.40 (5.77)***P	- 0.001 (- 0.74)	0.01 (0.21)	- 0.01 (- 0.77)	0.28 (1.77) *	0.03	0.02	214
HM	0.41 (7.08)***P	- 0.002(L_6) (- 2.55)**P	0.06(L_3) (2.27)**P	0.002(L_3) (0.30)	0 .35 (2.37) **P	0.09	0.07	208
SPAT	- 0.07 (- 0.28)	- .0-2 (-0.30)	1.15 (8.10)***P	0.09 (2.16)**P	0.64 (1.04)	0.14	0.12	214

The numbers in parentheses represent the t-statistic. The symbols *, **, and *** indicate a significance level of 10%, 5%, and 1%, respectively. The number of lags is presented by ($L_{\#}$). A letter P indicates a P-value of less than 5%.

Table 2. The Concurrent/ Lagged Results of the OLS Estimation –Dependent Variable: The Producer Price Index for Select Industries (Pre-and- Post COVID-19 Period: 2006-2023)

Dependent Variable	**Explanatory Variable Coefficient (t-statistic)**					**Other statistics**		
	Constant	**M2**	**EA**	**COP**	**V/U**	$\mathbf{R^2}$	**Adj.** $\mathbf{R^2}$	**No. of Obs.**
AC	0.30 (1.58)	- 0.002 (- 0.53)	0.27 (1.98)**P	0.30 (11.81)***P	5.92 (1.31)	0.59	0.58	215
AC	0.15 (0.86)	0.01(L_6) (1.89)*	0.33 (5.48)***P	0.30 (11.64)***P	5.30 (0.21)	0.60	0.59	209
IC	0.35 (1.73) *	- 0.01 (- 1.06)	0.21 (1.35)	0.32 (11.81)***P	5.97 (1.30)	0.60	0.59	215
IC	0.05(L_6) (0.13)	0.01(L_6) (2.17)**P	0.58(L_6) (2.12)**P	- 0.04(L_6) (- 0.91)	- 2.34(L_6) (- 0.27	0.06	0.04	209
TMI	- 0.18 (- 0.21)	0.001 (0.05)	0.04 (0.08)	1.35 (8.13)***P	1.18 (0.05)	0.49	0.48	215

AT	- 0.03 (- 0.06)	- 0.001 (- 0.23)	1.31 (3.49)***P	0.18 (2.11)**	17.58 (1.56)	0.09	0.08	215
NCD	- 0.19 (- 0.81)	0.02 (2.25)**P	81 (4.34)***P	0.09 (3.34)***P	2.22 (0.40)	0.12	0.11	215
AM	0.46 (7.30)***P	- 0.002(L_6) (- 2.31)**P	- 0.05(L_6) (- 1.87)*	0.02(L_6) (1.66)*	2.23(L_6) (0.94)	0.09	0.08	209
MESM	0.13 (5.72)***P	- 0.001 (- 2.58)**P	- 0.02 (-1.57)	0.01 (1.40)	2.27 (93.84)***P	0.09	0.07	215
PMM	- 0.16 (- 0.24)	- 0.004 (- 0.19)	1.89 (3.51)***P	0.26 (2.10)**P	26.41 (1.62)	0.09	0.07	215
GMSH	0.38(L_6) (8.70)***P	- 0.001(L_6) (- 2.10)**P	- 0.08(L_6) (- 3.61)***P	- 0.01(L_6) (0.22)	2.79 (1.96)*	0.03	0.01	209
OPH	1.40 (9.45)***P	- 0.01 (- 1.94)*	0.002(L_3) (0.04)	0.01 (0.56)	8.99 (1.25)	0.02	- 0.002	212
HM	0.46 (7.30)***P	- 0.01(L_6) (- 2.31)**P	- 0.05(L_6) (- 1.87)*	0.02(L_6) (1.66)*	2.22(L_6) (0.94)	0.09	0.08	209
SPAT	- 0.15 (- 0.62)	- 0.001 (- 0.19)	1.12 (7.86)***P	0.10 (2.26)** P	14.10 (1.87)*	0.14	0.13	215

The numbers in parentheses represent the t-statistic. The symbols *, **, and *** indicate a significance level of 10%, 5%, and 1%, respectively. The number of lags is presented by ($L_{\#}$). A letter P indicates a P-value of less than 5%.

Table 3. The Concurrent/ Lagged Results of the OLS Estimation –Dependent Variable: The Producer Price Index for Select Industries (Pre-COVID-19 Period: 2006-2018)

Dependen t Variable	**Explanatory Variable Coefficient (t-statistic)**					**Other statistics**		
	Constant	**M2**	**EA**	**COP**	**V/U**	**R^2**	**Adj. R^2**	**No. of Obs.**
AC	0.60 (3.28)***P	- 0.04 (- 5.45)***P	1.03 (1.80)*	0.214 (7.86)***P	0.68 (0.23)	0.69	0.68	147
IC	0.61 (3.41)***P	- 0.04 (- 5.92)***P	1.09 (1.87)*	0.23 (8.07)***P	0.25 (0.08)	0.71	0.70	147
TMI	- 0.79 (- 0.58)	- 0.03 (- 0.60)	5.03 (1.5)	1.46 (6.47)***P	- 17.55 (- 0.78)	0.61	0.60	147
AT	0.36 (0.59)	- 0.01(L_6) (- 0.60)	- 0.20 (- 0.09)	0.15 (2.77)***P	30.274 (2.56)***P	0.07	0.04	141
NCD	0.49 (-1.29)	- 0.01 (1.85)*	- 1.02 (4.36)***P	0.01 (2.95)***P	9.22 (0.76)	0.09	0.06	147
AM	-	0.01	0.94	- 0.01	- 0.65	0.24	0.22	147

	(1.43)	(2.39)**P	(- 0.44)	(- 0.30)				
AM	0.46(L_6) (4.84)***P	- 08(L_6) (- 2.62)***P	0.17(L_6) (0.67)	0.03(L_6) (2.02)**P	1.46 (0.58)	0.19	0.17	141
MESM	0.12 (3.62)***P	0.001 0.68	- 0.24 (-2.27)**P	0.01 (3.05)***P	2.38 (3.93)***P	0.12	0.10	147
PMM	-	0.01 (0.36)	0.83 (0.41)	0.19 (1.79)*	41.43 (2.46)***P	0.07	0.05	147
GMSH	0.37 (4.66)***P	0.002 (0.95)	- 0.41 (- 1.48)	0.01 (0.81)	0.60 (0.44)	0.02	- 0.01	147
OPH	1.45 (5.08)***P	0.01 0.63)	- 0.40 (-0.53)	0.02 (0.57)	16.71 (1.57)	0.03	0.00	147
OPH	-	0.03(L_6) (3.79)***P	3.71(L_3) (4.95)***P	- 0.05(L_3) (- 1.19)	- 8.64(L_3) (1.67)*	0.16	0.14	141
HM	0.32 (1.93)*	0.001 (0.16)	0.30 (0.41)	- 0.02 (-1.15)	0.50 (0.24)	0.05	0.02	147
HM	0.46 (4.89)***P	- 0.01(L_6) (- 2.62)***P	0.17(L_6) (67)	0.03(L_6) (2.02)**P	1.46(L_6) (0.55)	0.19	0.17	141
SPAT	-	2.48 (5.38)***P	262.01 (4.77)***P	4.42 (2.34)**P	- 411.79 (-1.83)*	0.67	0.66	147

The numbers in parentheses represent the t-statistic. The symbols *, **, and *** indicate a significance level of 10%, 5%, and 1%, respectively. The number of lags is presented by ($L_{\#}$). A letter P indicates a P-value of less than 5%.

Table 4. Significant Explanatory Variables Before COVID-19 (2006-2018) and the Entire Period (2006-2023)

Category	Period Before COVID-19 (2006-2018) Significant Explanatory Variable	The Entire Period Before and After COVID-19 (2006-2023) Significant Explanatory Variable
AC	M2(-), EA, COP	M2(L_6), EA, COP
IC	M2(-), EA, COP	M2(L_6)(-), EA(L_6)
AT	COP, V/U	EA, COP
SPAT	M2, EA, COP, V/U(-)	EA, COP, V/U
HM	M2(L_6)(-), COP	M2(L_6)(-), EA(L_6)(-), COP(L_6)
OPH	M2(L_6), EA(L_3), V/U(L_3)(-)	M2 (L_6) (-)
GMSH	None	M2(L_6)(-), EA(L_6)(-), V/U
PMM	COP, V/U	EA, COP
MESM	EA, COP, V/U	M2(-), V/U
TMI	COP	COP
AM	M2(-), EA, COP(L_6)	M2(L_6)(-), EA(L_6)(-), COP(L_6)
NCD	M2(-), EA(-), COP	M2, EA, COP

The number of lags is presented by ($L_{\#}$).

Table 5. Significant Dissimilar Explanatory Variables or Lags Before COVID-19 (2002-2018) and the Entire Period (2006-2023)

Category	Period Before COVID-19 (2006-2018) Significant Explanatory Variable	The Entire Period Before and After COVID-19 (2006-2023) Significant Explanatory Variable
AC	M2(-)	M2(L_6)
IC	M2(-), EA, COP	M2(L_6)(-), EA(L_6)
AT	V/U	EA
SPAT	M2, V/U	V/U
HM	COP	EA(L_6)(-), COP(L_6)
OPH	M2(L_6), EA(L_3)	M2(L_6)(-)
GMSH	None	M2(L_6)(-), EA(L_6)(-), V/U
PMM	V/U	EA
MESM	EA, COP	M2(-)
TMI	None	None
AM	M2(-), EA,	M2(L_6)(-), EA(L_6)(-)
NCD	M2(-), EA(-)	M2, EA

The number of lags is presented by ($L_{\#}$).

Table 6. Significant Identical Explanatory Variables or Lags Before COVID-19 (2002-2018) and the Entire Period (2006-2023)

Category	Period Before COVID-19 (2006-2018) Significant Explanatory Variable	The entire Period Before and After COVID-19 (2006-2023) Significant Explanatory Variable
AC	EA, COP	EA, COP
IC	None	None
AT	COP	COP
SPAT	EA, COP	EA, COP
HM	M2(L_6)(-)	M2(L_6)(-)
OPH	None	None
GMSH	None	None
PMM	COP	COP
MESM	V/U	V/U
TMI	None	None
AM	COP(L_6)	COP(L_6)
NCD	COP	COP

The number of lags is presented by ($L_\#$).

Table 7. The number of industries Significantly Affected by the Explanatory Variables

Table	Year	M2	EA	COP	D	V/U
One	2006-2023	4	10	7	6	n/a
Two	2006-2023	8	9	9	n/a	3
Three	2006-2018	7	7	10	n/a	5
Total		19	26	26	6	8

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ENTITLEMENT, WARMTH AND COMPETENCE IN PREDICTING THE RECEIPT OF HELP FROM ORGANIZATIONAL TEAMMATES

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ABSTRACT

Despite the growing body of work regarding psychological entitlement, little is known about how others act toward an entitled individual. Using a survey methodology, we examine how team members respond to an entitled peer. We find that perceptions of an individual's warmth and competence mediate the negative influence of the individual's entitlement on helping behaviors as directed toward the entitled individual. Considering the interpersonal nature of the current work environment and preponderance of entitled individuals in the workplace, this research underscores how an individual's entitlement not only affects their own behaviors, but also the behaviors of others within their group and/or organization.

INTRODUCTION

It can be frustrating and discouraging to work with individuals who perceive that they deserve more than others when it comes to their relationships and interactions (Campbell, Bonacci, Shelton, Exline, & Bushman, 2004). Researchers and the popular press have made the case that such perceptions of entitlement tend to be prevalent, and even increasing, among today's workers (Laird, Harvey, & Lancaster, 2015; Stein, 2013). This has interesting implications for modern organizations that tend to rely on team efforts and cooperation between employees in order to achieve desired outcomes (Devine, Clayton, Philips, Dunford, & Melner, 1999; Lawler, 1995).

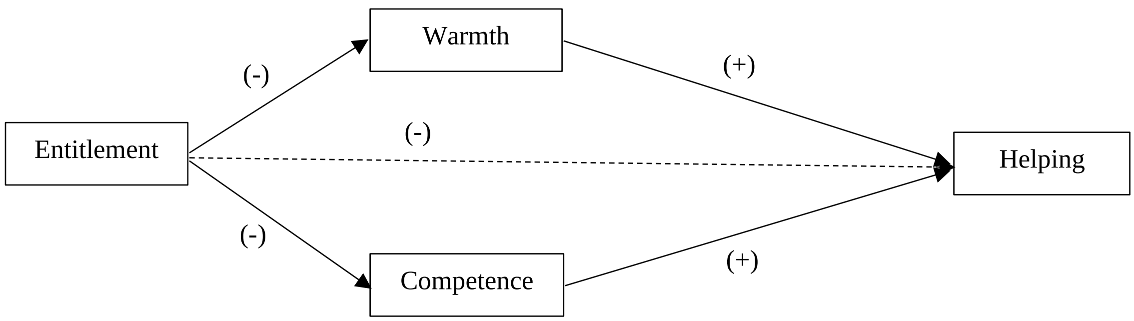
The interconnectedness of today's organizations has also increased interest in understanding factors that influence group behaviors (Cohen & Bailey, 1997; Stewart, 2010) such as the extent to which group members help each other. While existing research has identified many characteristics of an acting group member that influences their choice to perform helping behaviors, less is known about how a receiving individual influences the extent to which they receive help. Team members tend to choose how to behave toward an individual based upon the judgments that they make about the individual, for example the extent to which they like the person or see him or her as competent (Fiske, Cuddy, & Glick, 2007). Although team members may accumulate information about an individual from a number of sources, one salient source of information is likely the individual's own behaviors and self-expression (Jones & Shrauger, 1970). In associating with other people, individuals often communicate, either implicitly or explicitly, information that indicates their own self-views (Jones & Shrauger, 1970). As someone expresses their self-views, others will use this information as part of their evaluation of the individual.

A sense of entitlement is one of the factors others are likely to identify in the evaluation process. Entitlement is defined as an individual's belief that he or she deserves preferential rewards and treatment relative to others, often without consideration of abilities or performance levels (Harvey & Martinko, 2009). Entitlement is related to interpersonal deservedness and the objectification of others (Brown, Budzek, & Tamborski, 2009; Campbell, Goodie, & Foster, 2004). Individuals who are high on entitlement demonstrate little concern for the feelings of others (Zeigler-Hill, 2006), make self-serving attributions (Harvey & Martinko, 2009), and often view others as tools to accomplish their personal goals (Busch, Bell, Hotaling, & Monto, 2002). Entitled individuals also exhibit less loyalty, less empathy, and less perspective taking than their peers (Campbell, Bonacci, et al., 2004), and avoid getting emotionally attached to others (Tolmacz & Mikulincer, 2011). Entitled employees have a tendency to insult their coworkers (Harvey & Harris, 2010), get easily frustrated with others (Harvey & Harris, 2010), blame others for negative outcomes (Harvey & Martinko, 2009), and have difficulty forgiving others (Exline, Baumeister, Bushman, Campbell, & Finkel, 2004).

Overall, individuals exhibiting high entitlement have a tendency to put their own concerns above the concerns of others (Campbell et al., 2004a), frequently causing a more stressful working environment (Hochwarter, Summers, Thompson, Perrewe, & Ferris, 2010). If an individual's behavior is seen as selfish or indicative of low loyalty to the group then group members may also question the individual's intentions and develop negative attitudes towards the individual (Campbell, Bonacci, et al., 2004; Fiske et al., 2007). This often makes entitlement more interpersonally divisive than other traits (Carroll, HoenigmannStovall, & Whitehead, 1996). Although the prevalence of entitlement is well demonstrated, it is less clear how entitlement specifically influences the perceptions and behaviors of others.

We develop theory and predictions explaining why, in some cases, an individual's entitlement may lead them to receive fewer positive behaviors from others. The present research aims to test a model of how an individual's entitlement influences team member behaviors. We argue that an individual's level of entitlement will be negatively related to the amount of help that he/she receives from other members of his/her team, mediated by team member judgments of the individual's warmth and competence. We suggest that perceptions of an individual's entitlement will weaken team member beliefs regarding the individual's warmth and competence. These decreased warmth and competence perceptions will then lead team members to provide less help to the more entitled individual. Overall, we suggest that an individual's level of entitlement influences team member perceptions of and behaviors toward the individual.

Figure 1: Theoretical Model



THEORY AND HYPOTHESES

Individuals' ability to perform well at work is dependent upon not only their own knowledge and skills, but also their ability to garner support and resources from others within their group and organization. Although much of a team's effectiveness is due to individual in-role behaviors, a team's ability to function well is also dependent upon each person's decision to perform discretionary behaviors that benefit other individuals in the group (Organ, 1997; N. P. Podsakoff, Whiting, Podsakoff, & Blume, 2009; Smith, Organ, & Near, 1983; Van Dyne & LePine, 1998). Of the many types of discretionary behaviors, helping behaviors are one of the most typical and the most consistently related to workplace performance (Ehrhart, Bliese, & Thomas, 2006; Organ, Podsakoff, & MacKenzie, 2006). As a result, helping has been identified as one of the most important forms of organizational citizenship (P. M. Podsakoff, MacKenzie, Paine, & Bachrach, 2000). Interpersonal helping behaviors may include any discretionary work activities that involve actively assisting others, including altruism, courtesy, and most other behaviors that are directed at aiding specific individuals within the organization (Organ et al., 2006; P. M. Podsakoff et al., 2000).

Previous research has demonstrated that a number of factors influence an individual's participation in interpersonal helping behaviors. For example, the perceived fairness of group processes (e.g., punishment allocation) may increase the willingness of group members to help each other (Ball, Trevino, & Sims, 1994; Farh, Podsakoff, & Organ, 1990). Characteristics of the acting individual, such as their job attitudes, satisfaction, and mood may all influence their willingness to help others (Organ, 1994; Organ & Lingl, 1995; Smith et al., 1983). Personality factors such as the acting individual's level of agreeableness, conscientiousness, and social value orientation have also been positively related to their willingness to help others (Kamdar & Van Dyne, 2007; McClintock & Allison, 1989; Organ & Lingl, 1995). Despite a strong and growing literature on organizational citizenship behaviors, most research in this area has focused on characteristics of the individual enacting the behavior, neglecting the effect that the individual being helped has on his or her team member's decision to act (Lepine & Van Dyne, 2001).

Entitlement and Helping

Entitled individuals often create interpersonal hostility and conflict in their relationships (Moeller, Crocker, & Bushman, 2009). These individuals are also less loyal, more likely to insult or spread rumors about others, and more likely to become aggressive (Campbell, Bonacci, et al., 2004; Harvey & Harris, 2010; Reidy, Zeichner, Foster, & Martinez, 2008). These tendencies may explain why entitled individuals are often less secure in their relationships

(Tolmacz & Mikulincer, 2011), and why their relationships are typically shorter and of lower quality (Allen et al., 2009).

Relatedly, people with a high level of entitlement are likely to be viewed as less helpful. Team members tend to view helping as a reciprocal behavior, wherein they are more likely to help someone who they perceive will return the favor. Entitled individuals are often more selfish, competitively keeping critical resources from others, and may strategically withhold help when it benefits themselves (c.f., (Campbell, Bonacci, et al., 2004; Steinel, Utz, & Koning, 2010). If they believe an entitled individual is less helpful, or that the individual is likely to withhold help in the future, team members may be less willing to help that person. We suggest that individuals' level of entitlement will be negatively related to the amount of help that they receive from their peers.

> *Hypothesis 1: There will be a negative relationship between an individual's level of entitlement and the amount of help that team members give to that individual.*

Entitlement and perceptions of Warmth and Competence

Previous research suggests that most trait judgments fall along two dimensions of human cognition (Cislak & Wojciszke, 2008; Fiske et al., 2007; Fiske, Cuddy, Glick, & Xu, 2002; Judd, James-Hawkins, Yzerbyt, & Kashima, 2005; Kervyn, Judd, & Yzerbyt, 2009; Rosenber.S, Nelson, & Vivekana.Ps, 1968; Wojciszke, Bazinska, & Jaworski, 1998). The first dimension is comprised of perceptions related to an individual's warmth such as their trustworthiness, sincerity, kindness, and friendliness (Bargh, McKenna, & Fitzsimons, 2002; Cuddy, Fiske, & Glick, 2008; Fiske et al., 2007; Judd et al., 2005). These social judgments of an individual are related to the perceived intentions behind the individual's behavior (Fiske et al., 2002). If someone's intentions are seen as being aligned with the interests of others in the group then they will be judged as warm, but if their intentions are seen as self-serving then the person will be seen as cold (Cuddy et al., 2008).

The second dimension is related to the individual's competence and includes perceptions of their skill-level, creativity, confidence, and intelligence (Cuddy et al., 2008). While warmth judgments relate to a person's intentions, judgments of an individual's competence are based upon expectations of whether the person is capable of enacting their intentions (Fiske et al., 2002). For example, an employee may be paid to analyze their department's workflow, or they may conduct the analysis during their lunch break with an altruistic intention to improve their department's efficiency. Although the two scenarios represent different intentions, successful development of an analysis spreadsheet would indicate competence in both cases.

When group members observe an individual's actions, judgments along these two dimensions of warmth and competence account for a large proportion of the variance in how the individual will be evaluated (Wojciszke et al., 1998). Prior work has suggested that the way a person is judged influences the observer's subsequent actions toward that person (Cuddy et al., 2008; Fiske et al., 2002; Kelley, 1950; Kelley & Michela, 1980). For example, if an individual is seen as both competent and warm, then his or her peers will respond with admiration and a desire to cooperate with the individual (Cuddy, Fiske, & Glick, 2007). On the other hand, if the individual is seen as competent but low on warmth, or warm but low on competence, then his or her peers will respond with behaviors that are less positive and cooperative (Cuddy et al., 2008). In this way, judgments of an individual's warmth and competence can have a subsequent impact on the individual's ability to do his or her job.

There are two reasons to expect that individuals high on entitlement will be judged as lower in warmth. First, entitlement is associated with elevated, and often unrealistic, expectations regarding the work environment. As these expectations are unmet, the individual reevaluates his or her environment, often leading to negative dispositions and lower levels of job satisfaction (Naumann, Minsky, & Sturman, 2002). Judgments of an individual's warmth are largely dependent upon behavioral cues such as the frequency of smiling and making positive statements (Bayes, 1972). Yet, individuals with low satisfaction are likely to gripe about facets of their experience (Judge & Hulin, 1993) rather than focusing on things that are positive. We suggest that team members may interpret an entitled individual's disposition as an indicator of low warmth.

Second, previous research has demonstrated that entitled individuals are likely to exhibit individual differences associated with lower perceptions of warmth. For example, entitlement is negatively associated with levels of agreeableness (Campbell, Bonacci, et al., 2004; Pryor, Miller, & Gaughan, 2008), as well as self-report indicators of an individual's positive emotions (Pryor et al., 2008). As observers are often able to recognize personality traits, even in zero-acquaintance relationships, we predict these characteristics will be reflected in observer judgments of an individual’s warmth. As a result, an individual’s level of entitlement will be negatively associated with peer judgments of the employee’s warmth.

Hypothesis 2: There will be a negative relationship between an individual’s level of entitlement and team member judgments of the individual’s warmth.

In addition to assessing an individual’s warmth, group members also judge an individual’s competence. That is, competence judgments are also a fundamental part of the attribution process. Although observers may accept a person’s self-presentation and other observable cues at face value, these cues may also be filtered based upon other information regarding the target. Previous research has linked entitlement with selfishness, aggression, and even a willingness to take candy from children (Campbell, Bonacci, et al., 2004). Entitled individuals are also more willing to participant in morally questionable behavior such as cheating (Brown et al., 2009). As observers recognize these tendencies, they may be less open to information that reflects positively on the individual’s competence. Entitled individuals are also likely to be perceived as less prepared, as others may assume that entitled individuals did not work as hard and/or cut corners in their past experiences (e.g., cheated in school or relied heavily on the work of others). As a result, we suggest that an individual’s level of entitlement will be negatively associated with team member judgments of the individual’s competence.

Hypothesis 3: There will be a negative relationship between an individual’s level of entitlement and team member judgments of the individual’s competence.

Mediating Role of Competence and Warmth

As stated earlier, judgments of an individual’s competence and warmth account for a large proportion of the variance in how people evaluate behavior, and play an important role in determining how team members will react to an individual (Kelley & Michela, 1980). We relatedly suggest that perceptions of an individual’s warmth and competence stem from entitlement and are more proximal to helping behaviors than entitlement, thus filling a mediating role between perceptions of entitlement and coworker helping, facilitating an indirect negative relationship between an employee’s sense of entitlement and coworker behaviors (i.e., helping).

We suggest that tendencies related to reciprocity explain this mediation effect. Team members choose to help individuals who they believe both can and will reciprocate in the future (Konovsky & Pugh, 1994). The behaviors of entitled individuals are often viewed as lacking warmth (e.g., political and self-interested) rather than altruistically motivated (Harvey & Harris, 2010). If team members believe that an individual is acting on a personal agenda, they may choose to withhold help from that individual. Rather than helping, team members may even harm a cold individual (Fiske, Harris, & Cuddy, 2004). As a result, judgments of an individual’s warmth will mediate the relationship between an individual’s beliefs and a peer’s willingness to provide the individual help.

Hypothesis 4: Perceptions of an individual’s warmth will mediate the relationship between the individual’s level of entitlement and a team member’s willingness to help the individual.

Furthermore, a team member’s decision to help an individual is often based upon perceptions of the resources he or she believes the individual will bring to the relationship (Casciaro & Lobo, 2008). Because reciprocity is only possible when the individual has the correct skills to help in the future, team members may be more willing to help someone who they believe is competent than someone who is seen as incompetent. As discussed previously, we hypothesize that entitled individuals will be seen as lacking competence. We expect that judgments of an individual’s competence will thus mediate the relationship between an individual’s level of entitlement and the amount of help the individual receives from his or her team members.

Hypothesis 5: Perceptions of an individual’s competence will mediate the relationship between the individual’s level of entitlement and a team member’s willingness to help the individual.

METHOD

We tested the above hypotheses using a series of three surveys completed by individuals engaging in ongoing business project groups at a large Southern public university. Entitlement was collected in Survey 1 prior to formation of the groups. In survey 2, completed mid-way through the group project, members of the group were asked to make judgments of each group member’s warmth and competence. After the project had been completed, group members completed Survey 3, in which they reflected upon their helping behaviors toward each member of the group.

Participants

Potential participants for this study included approximately 510 individuals from 18 sections of a Business course at a large Southern public university. Survey 1 was completed by a total of 420 individuals, yielding an 83% initial response rate. A total of 403 individuals, a 79% response rate, then completed survey 2. Lastly, 379 individuals completed Survey 3, for a 74% response rate. Respondents had to answer questions on all three surveys and receive peer evaluations from both Survey 2 and Survey 3 to be included in the analysis. Of the initial 420 participants who completed Survey 1, a total of 272 (147 male and 125 female) received complete evaluations from at least three peers on both of the follow-up surveys and were included in the final analysis. The mean age of participants was 19.75 years. The overall inclusion rate was 54% of the initial sample, with a total of 87 groups of 4-6 individuals being represented in this study.

There were no significant differences between the initial sample, and the final participant group with regard to their gender (F=.44, p=.51), age (F=.32, p=.57), or level of entitlement (F=2.2, p=.14). There were also no significant differences in peer ratings of participants versus non-participants in terms of warmth (F=.27, p=.60), or help received (F=.03, p=.86). There was a difference in the perceived competence (F=7.28, p<.01) between the initial and final samples. This difference may be due to the included population having a greater number of judges than those excluded from the final sample, or the difference may be due to chance.

Procedure

Survey data were collected in three waves throughout the project to address the flow of effects within the model. Survey 1, was distributed during the first portion of the business project. It measured each participant's psychological entitlement and control variables such as the individual's age, gender, and overall GPA. Survey 2, containing the mediating variables, was completed midway through the business project. In Survey 2, participants confidentially gave their impressions of each group member's warmth and competence based upon their interactions together. Survey 3, containing the dependent variable, was completed after the project was finished but before individuals received formal assessments of their performance. In survey 3, participants were asked to confidentially rate the extent to which they helped each member of the project group.

Entitlement. We measured each individual's level of psychological entitlement with the 9-item self-rated psychological entitlement measure (Campbell, Bonacci, et al., 2004). This specific scale was selected because it has been found to be reliable, valid, stable across time, and unrelated to social desirability biases (Campbell, Bonacci, et al., 2004). On a scale of 1 –"Strongly Disagree" to 7 –"Strongly Agree," the participants were asked to evaluate items such as "I demand the best because I am worth it," Great things should come to me," and "I honestly feel I am just more deserving than others." There was a .85 Cronbach's alpha reliability estimate for the 9-items. The mean of this variable was 3.37 (*SD*=.97).

Warmth and competence. Perceived warmth and competence were computed as the average of at least three peer ratings of the individual's warmth and competence. On a scale of 1 –"Strongly Disagree" to 7 –"Strongly Agree," the participants were asked to evaluate the extent to which twenty-four trait adjectives describe each of their team members (Abele, Uchronski, Suitner, & Wojciszke, 2008). Perceived warmth was measured with terms such as "caring", "helpful", "sensitive", and "trustworthy." Perceived competence was measured with trait terms such as "able", "assertive", and "self-reliant." The Cronbach's alpha reliability estimates of the 12-item measure of perceived warmth and the 12-item measure of perceived competence were .90 and .90 respectively. The mean of the warmth variable was 5.71 (*SD*= .62) and the mean for competence was 5.58 (*SD*=.57).

We calculated inter-rater agreement for the warmth and competence evaluations that each member of the team received from their peers utilizing the rwg calculation (James, Demaree, & Wolf, 1984). We first calculated the observed variance for each of the participants who had received 3 or more peer ratings on both Survey 2 and Survey 3. Following common convention, we relied upon a uniform, or rectangular, null distribution, which for a 7-point scale gives an expected null variance of 4 (LeBreton, Burgess, Kaiser, Atchley, & James, 2003; LeBreton & Senter, 2008). The mean rwg for each variable was then calculated across all participants. The mean rwg values for perceived warmth and perceived competence were .69 and .67 respectively. These rwg values are lower than appear in other contexts due to the atypical use of this calculation. Whereas most examinations use rwg as a measure of agreement regarding a team-level factor, participants in this study were asked to evaluate individuals within the team. As dyadic relationships differ between individuals, one would expect variance in how team members experience and interpret an individual's behavior.

Help received. The extent to which an individual received help from their peers was measured using four items derived from Podsakoff, Ahearne, et al. (1997). This survey included questions about the group member's willingness to help each individual peer. With reference to peer X: each group member stated agreement on a scale of 1 – "Strongly Disagree" to 7 – "Strongly Agree", with the statements "I was willing to help X if he/she fell behind in his/her work", "I encouraged X if he/she were feeling down", "I was willing to take steps to try to prevent X from having problems", and "I willingly gave my time to help X with work-related problems." Help Received (the dependent variable), for person X, was then calculated as the mean of helping responses targeted at person X as rated by members of their group. In other words, Help Received is the average amount that others reported having helped person X. Cronbach's alpha reliability estimates of .82 were received for the 4-item measure of help given to the target. The mean of this variable was 5.92 (*SD* =.47).

Control variables. As mentioned previously, we collected each participants' gender, age, and GPA in Survey 1 to be used as controls in our analyses. Average participant age was 19.75 (*SD*=1.90), 54% of the sample was female, and the median GPA fit the category of "3.5-3.75".

Hypothesis Testing

We provide the means, standard deviations, and correlations in Table 1. Table 2 provides the results of our regression analyses related to Hypotheses 1-3. We tested these hypotheses using regression analysis in SPSS statistical software (version 23). Our analyses included gender, age, and GPA as control variables. As a robustness check to ensure that results could not be attributed to individuals being nested in class sections and groups, we also tested these hypotheses using regression analysis in R statistical software. These linear mixed effects models included gender, age, and GPA as control variables, and accounted for the multilevel nature of the data (i.e., class section and group membership of the individual), but were not used as the primary analysis as they do not allow for the calculation of R^2. The resulting coefficients were almost identical to the analyses conducted in SPSS and there were no meaningful changes in relation to the statistical significances of the relationships reported in Table 2. This suggests that the nested nature of our data did not influence the findings.

Table 1.
Means, standard deviations, and correlations

Variable	1	2	3	4	5	6	7
1. Age	–						
2. Gender	-.16	–					
3. GPA	.20**	.13*	–				
4. Entitlement (Time 1)	.07	-.05	.03	(.85)			
5. Warmth (Time 2)	.04	-.05	-.03	-.17*	(.90)		
6. Competence (Time 2)	.12*	.03	.00	-.14	.40**	(.90)	
7. Helping (Time 3)	.16**	-.04	-.05	-.00	.30**	.44**	(.82)
Mean	19.75	.46	4.72	3.37	5.71	5.58	5.92
Standard Deviation	1.91	.50	1.80	.97	.62	.57	.47

$^*p \leq .05$, $^{**}p \leq .01$.
Note: n=272. Internal consistency estimates are provided in parentheses.

We first examined the effect of the individuals' entitlement on peer behaviors toward the focal individuals. Hypothesis 1 suggested that an individual's level of entitlement would be negatively associated with the amount of help that the individual received from others. We do not find support for Hypothesis 1 (β = -.01, P= ns). We next considered the potential influence of an individual's entitlement on perceptions of the individual's warmth and competence. As predicted in Hypothesis 2, we found a negative relationship (β = -.17, P $\leq$ .01) between entitlement and perceptions of the individual's warmth. We also found support for Hypothesis 3, as entitlement was negatively related to the individual's perceived competence (β = -.14, P $\leq$ .05).

We then tested relationships relevant to Hypotheses 4-5. We first tested (Regression 4) to see if warmth and competence simultaneously predicted helping behaviors with psychological entitlement and the control variables included in the analysis. As predicted, both warmth (β = .16, P $\leq$ .01) and competence (β = .37, P $\leq$ .001) were significantly related to helping behaviors. As current thinking about mediation analysis does not require that a total effect be demonstrated prior to the estimation of indirect effects (Hayes, 2009; Hayes, Preacher, Tormala, & Petty, 2011), we considered the potential indirect effects from entitlement using bootstrapping to estimate the simultaneous direct and indirect effects of the individual's entitlement following the PROCESS procedure as outlined by Hayes (2012). Bootstrapping is a statistical method that estimates the parameters and standard errors of the model from repeated sampling of the initial data and estimating the indirect effect in each resampled data set (Preacher & Hayes, 2008). Bootstrapping is particularly useful for models where multiple mediators, for example both warmth and competence perceptions, are predicted to work simultaneously (Preacher & Hayes, 2008). When looking at the effect of entitlement on helping behavior, bootstrapped confidence intervals reveal a 95% bias-corrected interval that is entirely below zero through both warmth (-.03 to -.00) and competence (-.05 to -.00), demonstrating support for Hypotheses 4 and 5.

DISCUSSION

Theoretical Contributions

This research makes specific contributions to the literature on organizational citizenship behaviors (OCBs), of which peer helping is a component. Most of this literature describes characteristics of the actor that lead to their own helping behaviors (Konovsky & Organ, 1996; Lester, Meglino, & Korsgaard, 2008; Organ, 1994). While external influences on citizenship behaviors have been considered, previous research has focused on the collective support or antagonism from all coworkers rather than simply the individual receiving assistance (Chiaburu & Harrison, 2008). This research shows more specifically how the target's characteristics influence the amount of help that he or she receives. While an individual's willingness to perform citizenship behaviors has clear implications for both personal and team performance, the ability to solicit citizenship behaviors from others may be equally important.

Finally, this research takes a step in identifying the psychological mechanisms that influence an actor's behavior as directed toward a specific individual. Although perceptions of the target's warmth and competence are not the only perceptions that influence peer behaviors, these two dimensions of social judgment are important to understanding interpersonal behavior (Cuddy et al., 2008; Fiske et al., 2007; Judd et al., 2005). We found that perceptions of both an individual's warmth and competence are positively associated with that individual receiving help from others. We also discovered that an individual's feelings of entitlement indirectly influence others' behavior through peer judgments of the individual's warmth and competence. These findings suggest that rather than focusing only on the relationship between an individual's characteristics and peer behaviors, it is important to consider how characteristics of the individual influence interpersonal judgments.

Limitations and Future Directions

The behavioral outcome examined in this investigation was the average helping behavior within a group - as directed toward a specific member of that group. There are a number of challenges inherent in this type of investigation. An actor's helping behavior fluctuates over time dependent upon certain interpersonal perceptions (Spence, Ferris, Brown, & Heller, 2011), yet individual actor differences also supply a degree of consistency in their behavior (Organ & Lingl, 1995). In other words, although each target differentially influences the actor's behavior, it is difficult to deny that there is also be a strong actor effect. Furthermore, by examining the average amount that others helped a specific person, there is some assumed consistency in the communication between the target and each of his or her peers. It is alternatively possible that the target maintained different relationships with each team member, in some cases masking or illuminating their level of entitlement.

Because interactions within teams are often filled with such complexities, it may be easier to conduct future research of this type focusing on a dyadic setting. An examination of purely dyadic relationships outside of a team context would allow researchers to consider behaviors directed toward a singular target while controlling for more general tendencies. This suggestion should be taken with a degree of caution. While many corollaries may be drawn between groups and dyads, there are also many differences. For example, groups tend to be less tolerant of negative coworkers than individual judges (Liden et al., 1999). As a result, the detrimental consequences of entitlement, as seen in a team context, may not appear to the same extent within dyadic relationships.

In our investigation warmth and competence perceptions were examined as mediators of the relationship between the individual's psychological entitlement and team member behavior, yet other mechanisms may also help in understanding this relationship. We encourage researchers to examine other perceptual, psychological, and behavioral mediators that may explain the associations that we observed. Our theoretical arguments suggest that coworker judgments are formed as a response to the individual's beliefs, but only to the extent that those beliefs influence the individual's behavior. This suggests a number of potential moderators for future examination. Individual characteristics, such as impression management skills, may diminish the effect of entitlement on team member judgments. Even if an individual believes that they are more deserving than others, they may put up a façade or carefully choose behaviors that will not portray this belief to others. The individual's level of discretion may also influence their behaviors, and as a result affect the relationship between the individual's beliefs and team member reactions. Furthermore, in addition to an individual's behavior, team members often consider the outcome of that behavior when determining their response (Alicke, Davis, & Pezzo, 1994; J. Baron & Hershey, 1988). Research examining behaviors as a potential mediator should also consider the interaction of the chosen behavior with the valance of its outcome.

Group tenure may also influence the relationship between an individual's beliefs and peer behaviors. Team members in newly formed groups may accept an entitled individual's self-presentation, yet these impressions can wear on team members over time and be more destructive in the long term (Paulhus, 1998). As a result, the length of time that the group has been together may influence the relationship between an individual's beliefs and peer behaviors.

While this research offers several new insights into our understanding of behavior within groups, future research could expand the model to include group performance. It has been suggested that the actions of a single team member may serve as a catalyst for team-level dysfunction (Felps, Mitchell, & Byington, 2006). In addition to the individual's actions, this research shows that an individual's beliefs, such as their level of entitlement, can negatively affect peer behaviors. The amount of helping behavior within a team has been positively linked with overall team performance (Choi, 2009; Philip M. Podsakoff, Ahearne, & MacKenzie, 1997), and performance may suffer whenever factors, such as an individual's level of entitlement, decrease helping behaviors.

Future research might also explore these ideas outside the university context where egocentric beliefs are especially prevalent. While any individual may hold egocentric beliefs, the prevalence of these beliefs differs across populations. Prior research shows that individuals currently in college tend to score higher than those who graduated earlier and are currently in the work-force (Twenge, Konrath, Foster, Campbell, & Bushman, 2008). In her book "Generation Me," Twenge (2006) points out that egocentric actions are not stigmatized in the eyes of the current generation the way they were a few years ago. Although the prevalence of individuals in the sample with high entitlement may be greater than the general population, the permissibility of these egocentric self-views by this demographic makes it a potentially more conservative context in which to test this theory. The influence of entitlement may be more salient, and have a greater influence on interpersonal outcomes, when examined in older populations. In addition, our university sample may have influenced our findings of age as a significant predictor of receiving help and being perceived as competent (depicted in Table 2). It is possible that in a university setting, where age is fairly homogeneous, differences in age may elicit stronger responses from peers. For example, an individual returning to complete a degree after serving in the military might be perceived as especially competent and worthy of help.

PRACTICAL IMPLICATIONS AND CONCLUSIONS

In addition to contributing to the current literature, this examination has practical implications for groups and organizations. In the recruiting and selection process, indications of a potential employee's personality characteristics may be nearly as influential as their general mental ability (Dunn, Mount, Barrick, & Ones, 1995). Businesses may be tempted to similarly use indications of an individual's entitlement as predictors of future success, and treat these views as informative when choosing whom to hire. Individuals who show tendencies toward entitlement are likely to cause future problems in their interactions on the groups that they join, and are less likely to contribute to their group's success when helping between group members is important to outcomes.

This research might also benefit individuals who recognize their own egocentric tendencies. New (e.g., recent college graduates) and experienced employees often do not perceive the potential damage associated with focusing on themselves in a group context (Twenge, 2006). This research shows, rather ironically, that an individual's belief that he/she deserves preferential treatment can indirectly decrease the amount of assistance that he/she actually receives from others in a group. By highlighting the immediate and very tangible consequences of demonstrated entitlement, entitled individuals may recognize a need to buffer their own self-expression when working with others in a group setting.

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RESEARCH NOTES

THE TECHNOLOGICAL IMPACT OF PATENT CLASSES AND THE INNOVATION TRAJECTORIES OF FIRMS AND LOCATIONS

Thomas D. Craig, DeSales University

ABSTRACT

The technological impact of innovations is commonly measured using forward citations linked back to individual patents, or forward citations linked to portfolios of patents at the firm level. Taking a different approach, this study calculates impact at the patent classification level, revealing the changing importance of each underlying technology category over a 40-year period. Applying the calculated class- and subclass-level impact values from each year to firm and location patent histories, the evolving impact trajectories of firms and locations can be observed and quantified to provide new insights into historical patterns of innovation.

INTRODUCTION

Understanding the nature and scope of inventive, innovative, and imitative activity within business units, firms, and geographic regions, and how these characteristics differ and change over time, is of central importance to innovation and strategic entrepreneurship research. It is generally accepted that organizations that consistently exhibit more – and more impactful – entrepreneurial behaviors should outperform their less-entrepreneurial counterparts (Ireland et al., 2003). Recent efforts to clarify these phenomena include investigations into the quality, economic value, and spillover effects of university patents (Kolympiris & Klein, 2017), the patterns and implications of the decline in upstream scientific exploration within firms and corporate labs (Arora et al., 2018), and the effects that imitative efforts by new entrants have on incumbent firm performance (Wang et al., 2019). The potential and realized economic value of these and other exploration efforts is an important factor in decision making by entrepreneurs, managers, investors, and policy makers (Arora et al., 2018).

A critical component of research in this area is the extensive set of tools and measures used to determine the level and impact of exploration, innovation, and entrepreneurship activity in individuals, firms, locations, and other focal units of analysis. Over the past several decades, numerous measures, scales, and indices have been developed from a broad range of perspectives, including simple patent counts and weighted patent counts (Griliches, 1990; Trajtenberg, 1990), patent scope (Lerner, 1994), patent impact (Rosenkopf & Nerkar, 2001), entrepreneurial orientation (Covin & Slevin, 1989; Lumpkin & Dess, 1996; Miller, 1983), and strategic entrepreneurship behaviors (Anderson et al., 2019).

While the effectiveness and limitations of using patent data have been the subject of debate for many years (Acs & Audretsch, 1989; Alcácer & Gittelman, 2006; Criscuolo et al., 2019; Gittelman, 2008; Roach & Cohen, 2012), patent and citation analysis is still widely used and accepted by scholars in entrepreneurship and innovation studies. Forward citations are a benchmark measure of the technological and commercial importance of patents. A review by Aristodemou and Tietze (2018) identifies nine particularly relevant forward citation-based measures of impact, which they categorize as either patent level or patent portfolio level measures.

This study takes a different approach and calculates a new measure of impact at multiple patent classification levels over a 40-year period, yielding two main benefits. First, by developing an aggregate yearly measure of impact that considers all patents in each particular class and subclass, the historical pattern of importance for each underlying technology can be tracked. Second, by applying the calculated yearly impact values for each class and subclass to the patent histories of firms and locations, the yearly impact and historical pattern of impact for each firm and location can be observed and quantified in a new way. New constructs and methods of measuring entrepreneurial activity and its effects are "central to the field, and central to answering the questions we ask as strategic entrepreneurship scholars" (Anderson et al., 2019, p. 200). This study contributes to the literature by developing a new method of measuring entrepreneurial activity and applying it to provide new insights into the innovation activities of locations and firms.

DATA SOURCES

Patent data for this study were obtained primarily from the United States Patent and Trademark Office PatentsView website (https://www.uspto.gov/ip-policy/economic-research/patentsview). Additional supporting data were obtained from the NBER Patent Data Project (Hall et al., 2001), the NBER U.S. Patent Citations Data File, Compustat, EDGAR, and individual firm websites.

Patent classes used in this study are based on the Cooperative Patent Classification (CPC) system (https://www.cooperativepatentclassification.org), a joint endeavor between the European Patent Office (EPO) and the USPTO. The CPC defines patent classifications at multiple levels of granularity, as articulated in the USPTO PatentsView bulk downloads data dictionary for the "*cpc_current*" table. Table 1 illustrates these distinct levels of patent classification. The full Cooperative Patent Classification code set and details are available at https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html.

Table 1: Example of the multi-level patent classification coding in the CPC system
A patent that is assigned a full CPC classification code of "A61B 3/00"
comprises the following four levels of specificity:

Class Code	Data Element Name	Class Description
A	*section_id*	Human Necessities
A61	*subsection_id; "class"*	Medical or Veterinary Science; Hygiene
A61B	*group_id; "subclass"*	Diagnosis; Surgery; Identification
A61B 3/00	*subgroup_id*	Apparatus for testing the eyes; instruments for examining the eyes

Within the CPC coding system, many *subgroup_id* classifications have even further subclassifications. For example, within *subgroup_id* "A61B 3/00" there are currently 11 additional subclassifications, including "A61B 3/0008" which indicates "Apparatus for testing the eyes; Instruments for examining the eyes - provided with illuminating means". Calculating impact at this extreme level of granularity was not pursued in the present study. The top CPC classification level, *section_id*, with only nine distinct classes (e.g. "A – Human Necessities") was deemed too generalized to provide meaningful insights for this study, and was excluded from further consideration. Similarly, *subgroup_id* was deemed too specific and was also excluded. Covering the years 1975-2014, the final dataset for the class and subclass impact calculations included 125 unique class codes and 4,982 class-year combinations for *subsection_id*, and 653 unique subclass codes and 24,733 subclass-year combinations for *group_id*.

Over 6.8 million issued patents and over 21.6 million citation pairs from 1975 to 2019 were analyzed. Patents and citation pairs from years 2015 to 2019 were included to capture forward citations within five years for the cited patents issued through 2014. Further analysis and processing of the data produced the impact values at two levels of granularity, corresponding to the CPC classifications outlined in Table 1 (*subsection_id* and *group_id*, henceforth referred to as "class" and "subclass", respectively). For the remainder of this paper, the discussion is focused primarily on the *group_id* or "subclass" level only, but the methodology described can be applied to all classification levels. Unless specified, the term "class" is used to indicate both class and subclass levels.

HOW CLASS AND SUBCLASS IMPACT VALUES ARE CALCULATED

The impact values for each class and subclass were created by combining and cross referencing elements of multiple files from the USPTO PatentsView website, the NBER Patent Data Project (Hall et al., 2001), and the NBER U.S. Patent Citations Data file that separately contain data for each patent including assignee(s), application and grant dates, patent class assignments, and citation pairs. Unless noted, patent application (filing) dates were used in all calculations.

Following prior research, steps were taken to address the inherent "noisiness" and limitations of patent and citation data. For example, because each patent can be assigned multiple CPC classes which would improperly inflate the counts of cited and citing patents in each class, fractional patents were calculated based on the number of classes assigned to each patent (Rosenkopf & Nerkar, 2001). In addition, time limits on forward citations are commonly used to improve the calculation of impact and avoid truncation bias from citations that continue to be received at a nondeclining rate (Hall et al., 2005). Accordingly, forward citations were limited to those within five years of the cited patent application year. Consistent with prior studies (e.g. Miller et al., 2007; Rosenkopf & Nerkar, 2001), self-citations were also excluded from the impact calculations.

In many prior studies, the technological impact of individual patents has been measured by the number of forward citations a focal patent receives compared to other patents in the same period (Ahuja & Lampert, 2001; Argyres & Silverman, 2004; Kolympiris & Klein, 2017; Onal Vural et al., 2013; Rosenkopf & Nerkar, 2001; Trajtenberg, 1990). To calculate impact at the class level, the single-patent impact logic is extended to identify in each year the total number of patents issued in each class, and the total number of forward citations associated with the patents issued in each class. Following the single-patent approach to measure impact used in prior studies (Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001), the ratio of all fractional forward citations to all fractional patents issued in each class was calculated to be the total impact value for each class in each year.

To standardize the calculated impact values which have different ranges each year, all impact values were assigned to one of ten mutually exclusive bins that evenly divide the impact range of each year into equal intervals, or "buckets". Each patent class then was assigned (based on its impact value) to its corresponding impact bucket in each year over the 1975–2014 period, with the impact bucket "1" containing the most impactful patent classes (with the highest ratios of forward citations to issued patents), and the impact bucket "10" containing the least impactful patent classes (with the lowest ratios of forward citations to issued patents). The aggregation of patent class, year, and impact bucket data for all years and classes provides the full impact summary list, an excerpt of which is shown in Table 2. Figures 1(a) and 1(b) depict a graphical application of this data.

Table 2: Selected impact summary data (1975–2014)

This summary includes the number of patents issued (full and fractional), 5-year forward citations, calculated impact, and the impact bucket for each CPC patent subclass and year.
The impact buckets range from 1 ("most impact") to 10 ("least impact").

CPC Subclass	Year	Patents Issued (full)	Patents Issued (fractional)	Forward Cites (fractional)	Impact (FC/Patents)	Impact Bucket
A63B	2002	1,627	1,316.58	1,688.80	1.283	7
A63B	2003	1,640	1,338.17	1,695.90	1.267	6
A63B	2004	1,578	1,288.20	1,647.20	1.279	5
A63B	2005	1,450	1,177.65	2,069.87	1.758	3
A63B	2006	1,320	1,066.75	1,774.53	1.663	3
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B41J	2003	2,528	1,988.58	3,267.00	1.643	5
B41J	2004	2,704	2,117.13	3,064.83	1.448	4
B41J	2005	2,700	2,133.33	1,977.48	0.927	6
B41J	2006	2,512	2,041.23	1,663.52	0.815	6
B41J	2007	2,514	2,010.70	1,539.22	0.766	7

APPLICATIONS OF THE CLASS AND SUBCLASS IMPACT VALUES

The comprehensive, standardized listing of yearly impact values and buckets for each patent class from 1975 to 2014 can be combined with other patent details and used to better understand multiple areas of interest to innovation and strategic management scholars. These include the evolving impact of technologies, firms' exploration strategies and outcomes, and geographic comparisons of innovativeness over time.

The Evolving Impact of Technologies

The impact values can be used to track the emergence of technologies represented by each patent class and their changing impact over time. To illustrate, the increasing and decreasing impact of multiple patent classes are depicted in the figures below.

Since the 1980s, the class of patents representing inventions and innovations in physical training, gymnastics, and related fitness equipment (Class A63B: Figure 1(a)) experienced an upward trend in calculated impact, i.e. the ratio of forward citations to issued patents. Not surprisingly, over the same period the class of patents representing inventions and innovations in typewriters and other less-advanced printing devices (Class B41J: Figure 1(b)) experienced a decline in impact on subsequent innovations, as newer tech

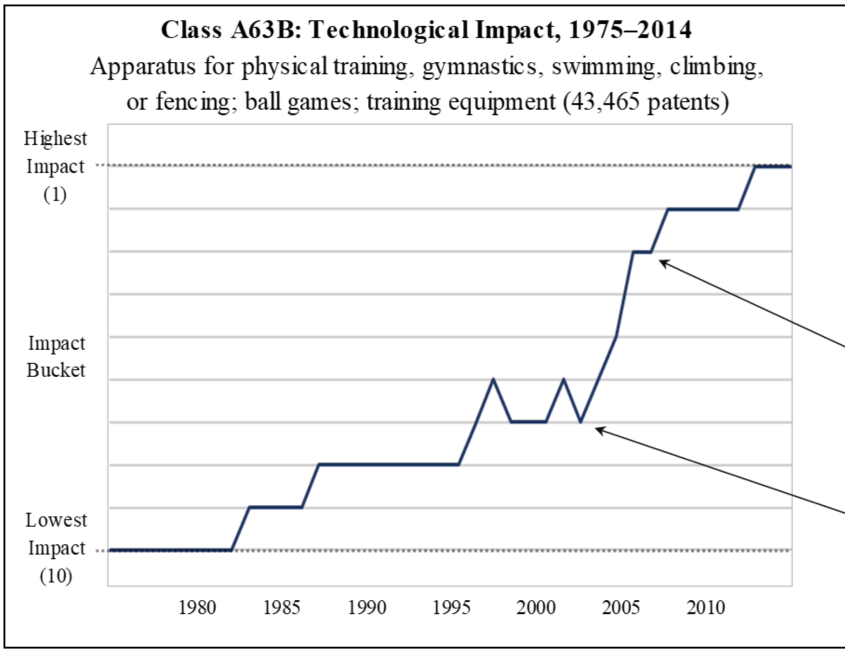


Figure 1(a):
Data points on these graphs correspond to the calculated impact bucket for the class in each year (see Table 2 above).

For example, in 2006 the calculated impact bucket for class A63B is "3", i.e. the "3rd highest impact group" of that year.

In 2002 the calculated impact bucket for class A63B is "7".

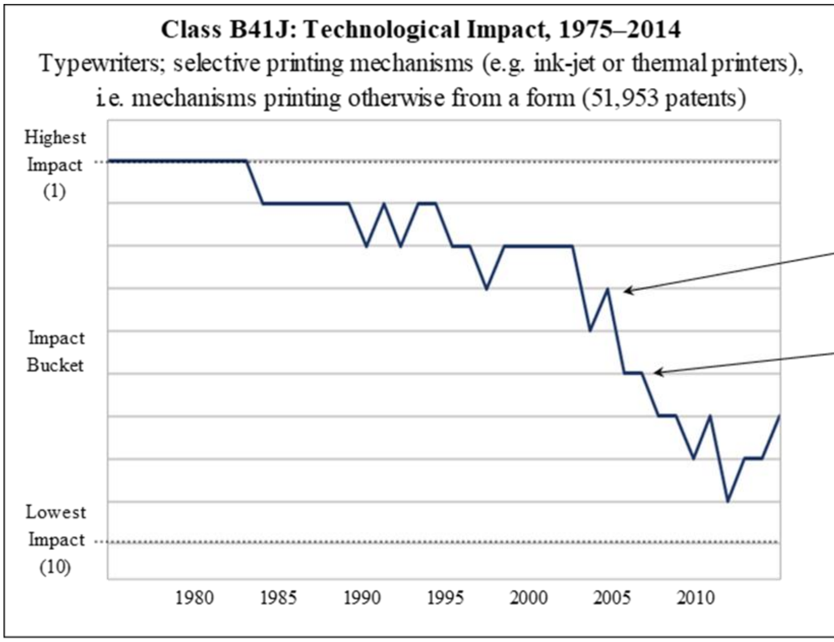
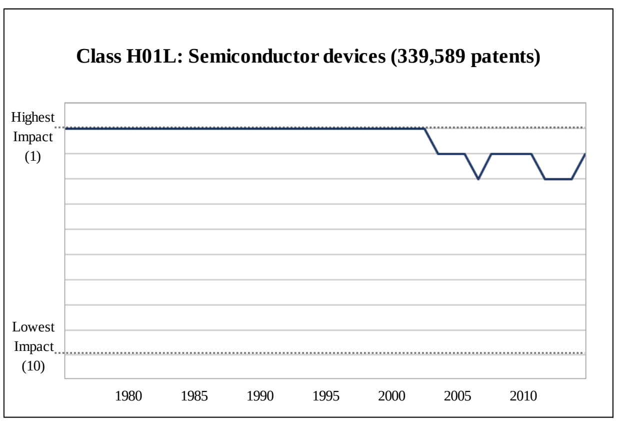


Figure 1(b):
(from Table 2 above)

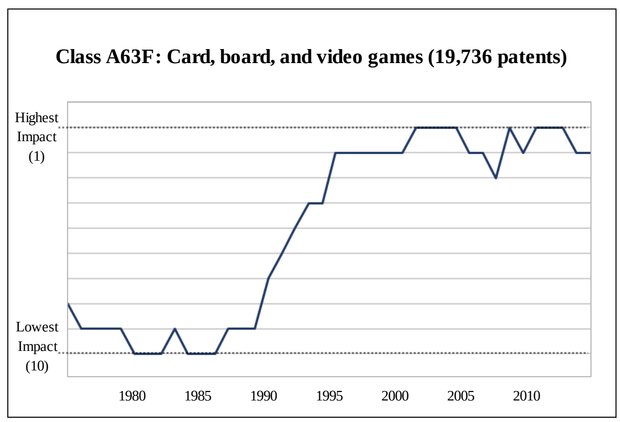
In 2004, the calculated impact bucket for class B41J is "4".

In 2006, the calculated impact bucket for class B41J is "6".

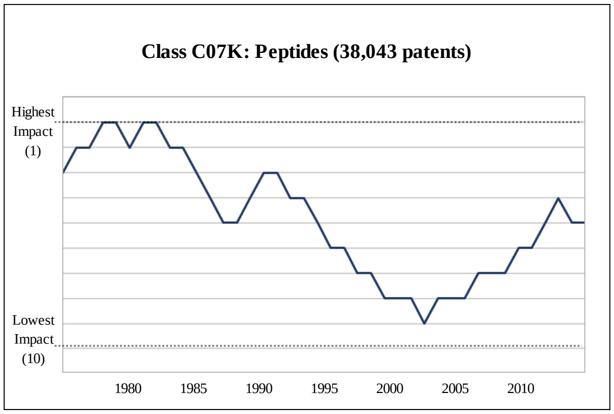
As shown in Figures 2(a) – 2(d), the calculated class impact values reveal the changing and steady states of technological impact related to innovations and industries that are both well-known in the business press and academic literature (e.g. semiconductors and video games), and less well-known (e.g. peptides and grinding machines).



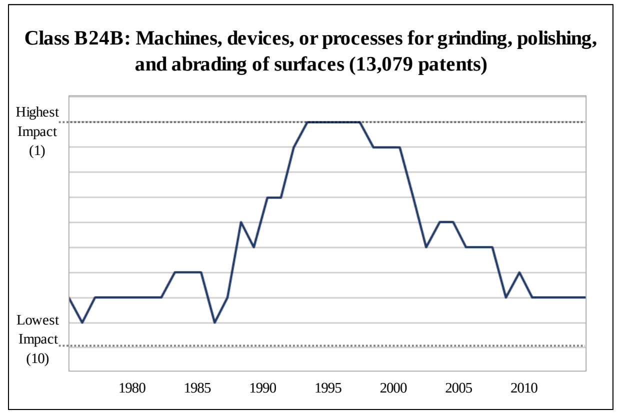
2(a)



2(b)



2(c)



2(d)

Firms' Strategies for Innovation

In addition to tracking the evolving impact of individual technologies, the class impact values can be used to identify and measure differences in exploration strategies and compare the results of R&D investments and innovation outcomes among firms, and within firms over time. To demonstrate this, the calculated impact level or "bucket" of each patent class in each year was assigned to every patent in the PatentsView database. All patents associated with each firm and class were then grouped and summarized, and the proportion of fractional patents in each impact bucket (out of the firm's total patent count) for each year was calculated and graphed.

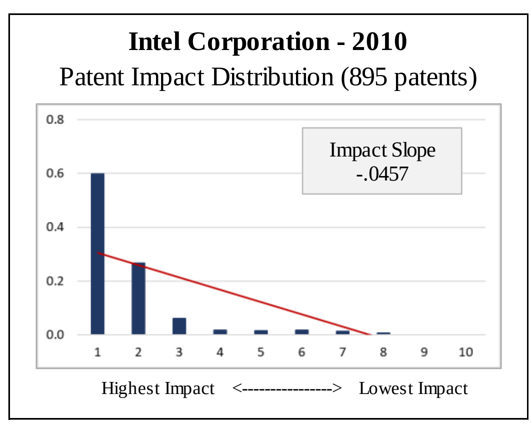
The result of this analysis method provides a visually intuitive bar graph (Figures 3(a) – 3(c)) that shows the proportions of a firm's total patents across the impact scale in each year, in classes that range from having the most downstream impact (bucket = 1) to the least downstream impact (bucket = 10). Adding a fitted line to the range of values provides a single measure (the impact slope) that captures the unique underlying "shape" and distribution of the firm's patenting impact for that year. The impact slope value is a standardized firm-year measurement that can be used to describe and compare a firm's overall innovation activity or outcomes, and can be used as an independent, dependent, or control variable in further analyses.

In Figures 3(a) – 3(c), the aggregate patenting activity of Intel, Boeing, and Xerox in the year 2010 is displayed for comparison. In that year, the majority (nearly 60%) of Intel's 895 patents were in the highest impact patent classes (bucket 1) of 2010, with most of the remainder in the second and third most impactful classes. The predominance of patents in higher impact classes yields a negative impact slope value (-.0457) for Intel in 2010. Boeing's 635 patents were more dispersed than Intel's across the impact spectrum in 2010 (but still in mostly higher impact classes), while Xerox's 694 patents were spread more evenly across the impact spectrum, yielding a near-zero impact slope value (.0008) for Xerox in 2010. The graphs and impact slope values suggest that, comparatively speaking, despite having fewer patents Boeing generated greater innovation impact than Xerox in 2010, but proportionally less impact than Intel in that particular year.

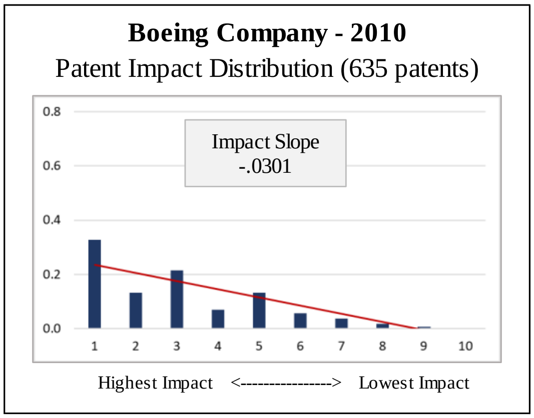
In 2010, the Intel Corporation had a total of 895 fractional patents in all patent classes.

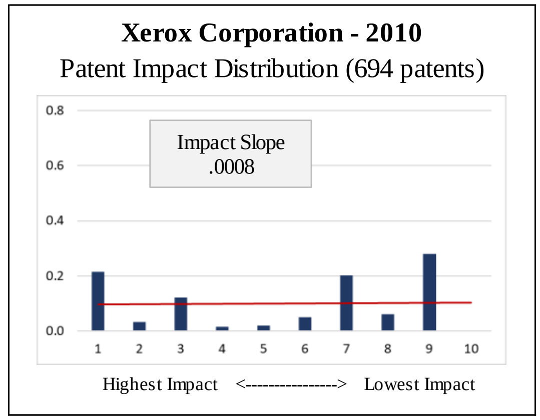
Of these, 59.9% were in the highest impact classes for that year (bucket = 1), 26.7% were in the 2nd highest impact classes (bucket = 2), and 6.1% were in the 3rd highest impact classes (bucket = 3).

The impact slope value provides a unique, standardized firm-year measure of the distribution of a firm's patenting activity and impact in each year.



3(a)

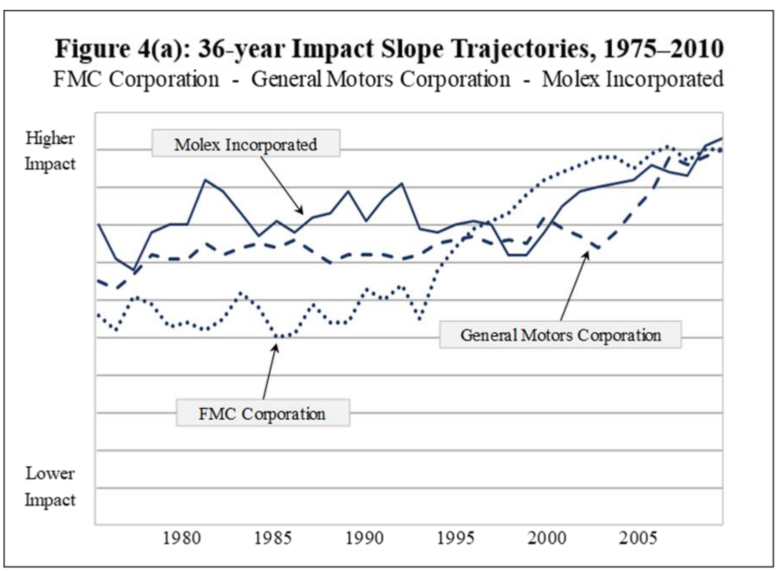


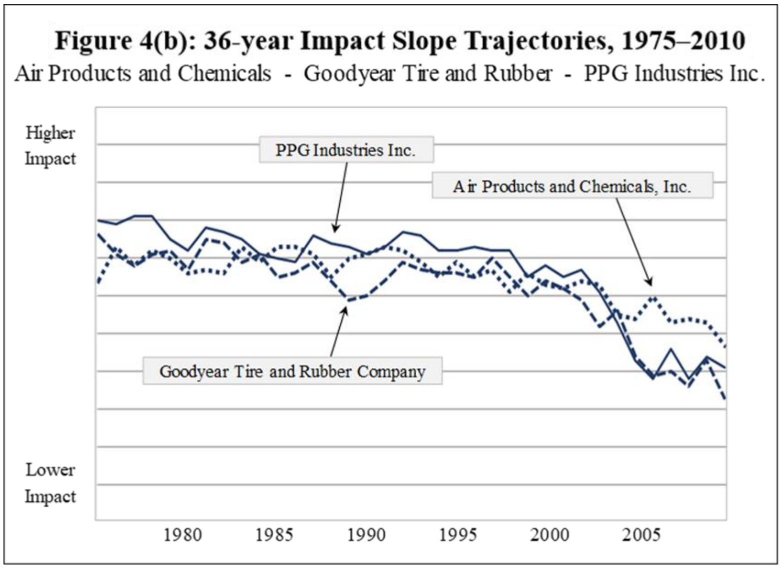


3(b)

3(c)

In addition to providing a standardized measure of the single-year impact generated by firms as described above, the impact slope values for each firm over time can be plotted to reveal longitudinal patterns of increasing, decreasing, or stable impact. For example, in Figure 4(a) the rising impact slope trajectories of FMC, General Motors, and Molex indicate that these firms were over time generating increasingly greater proportions of patents in higher impact classes. In Figure 4(b), the impact slope trajectories of Air Products, Goodyear, and PPG Industries indicate that these firms were over time increasingly generating greater proportions of patents in lower impact classes. Further research using the impact values and slope calculations can clarify whether these patterns reflect strategic shifts by the firms to exploration in different (higher or lower impact) technologies, shifts in the impact level of technologies already being pursued by the firms, or both.





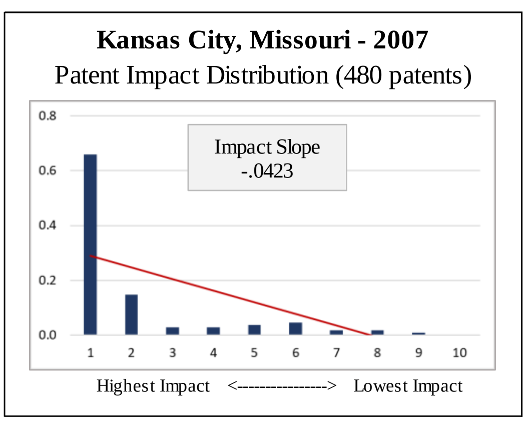
Geographic Differences in Patenting Impact

The patent class impact values can also be used to examine the emergence, growth, and decline of innovative importance in geographic regions over time, and to compare impact between regions. Similar to the method for measuring the overall impact of a firm's patenting activity, all patents in the USPTO PatentsView database are linked with a specific geographic location based on latitude and longitude data from the patent file and corresponding metropolitan area coordinates. These data are grouped and summarized, and the proportion of patents in each impact bucket (out of the geographic location's total patent count) for each year is calculated.

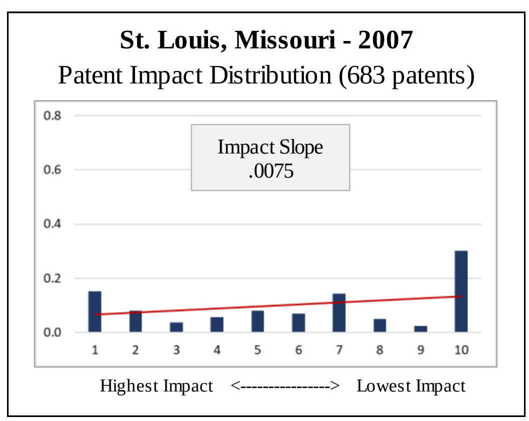
In the (geo)graphical examples below (Figures 5(a) – 5(d)), the impact distributions of patenting activity in 2007 from several metropolitan areas are displayed for comparison. In that year, patenting activity in Kansas City, Missouri and Iowa City, Iowa was predominantly in higher impact technologies; 65.9% of Kansas City's 480 patents issued in 2007 were in the highest impact classes of that year.

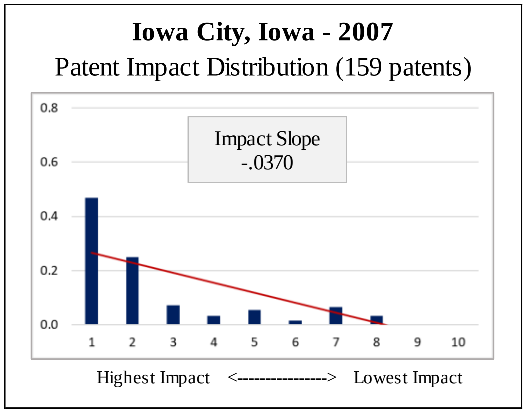
Conversely, most of the patenting activity in St. Louis, Missouri and Des Moines, Iowa was in lower impact technologies; 71.6% of Des Moines' 186 patents issued in 2007 were in the lowest impact classes of that year.

5(a)

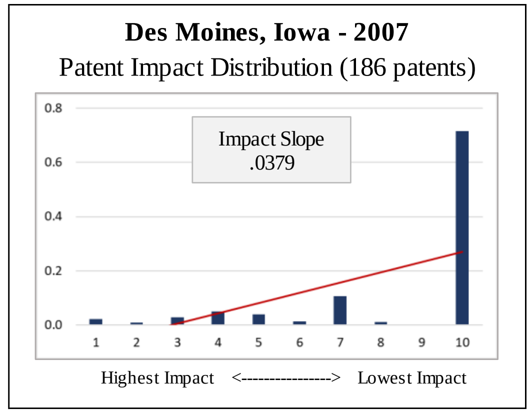


5(b)





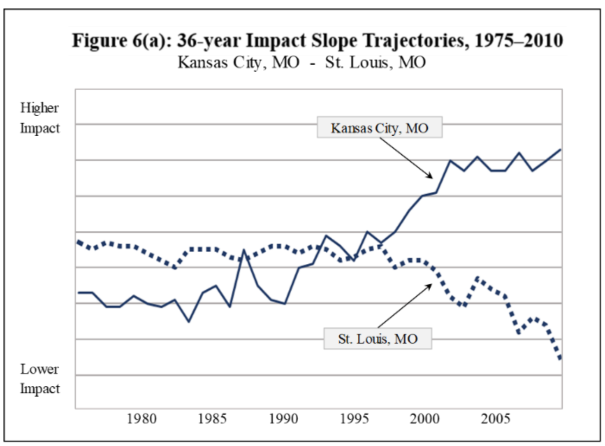
5(c)

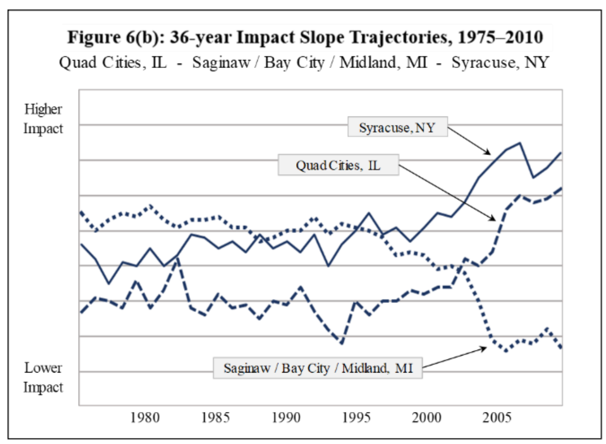


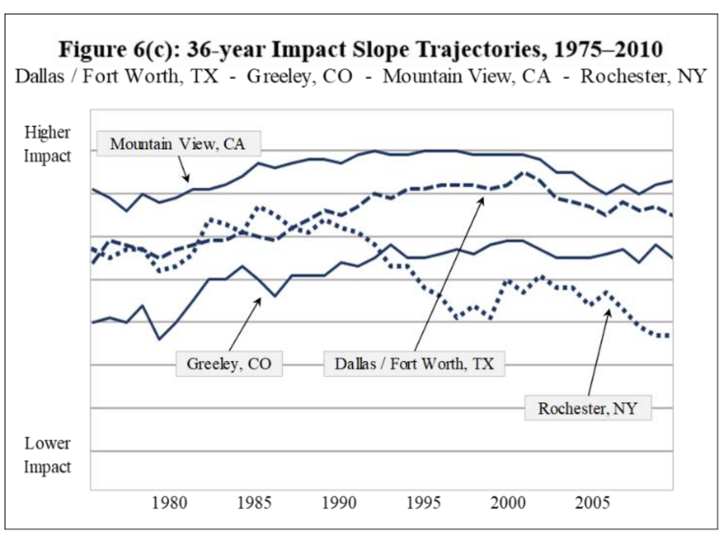
5(d)

As with the firm-level calculations, the impact slope value for each location-year combination is a unique standardized measurement that can be used to describe and compare the overall innovation activities or outcomes for each location, and can be used as an independent, dependent, or control variable in further analyses.

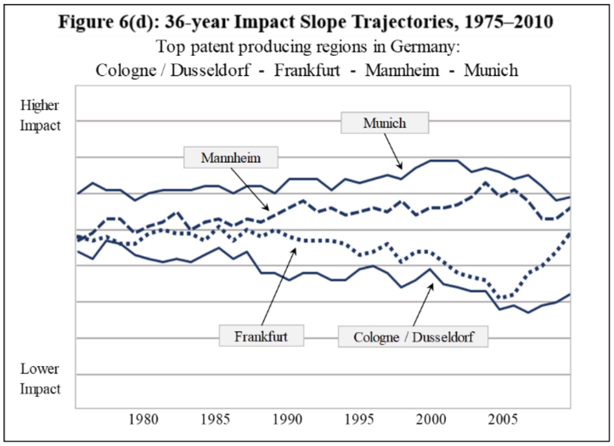
Plotting the impact slope values for each location over time, similar to the process used with firms, reveals longitudinal patterns of increasing, decreasing, or stable impact. Figures 6(a), 6(b), and 6(c) depict the diverging impact trajectories of Kansas City, St. Louis, and other high-volume patenting cities in the United States, indicating periods of both change and relative stability of technological impact in these locations over the last several decades.

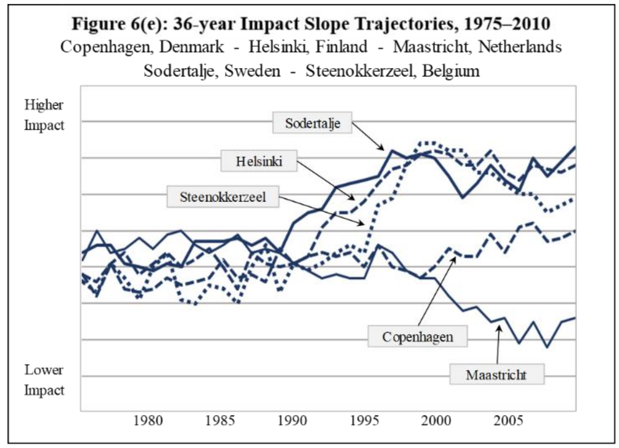






In Figure 6(d), the longitudinally plotted impact slope values of the top four patent-producing regions in Germany show these cities maintaining consistently distinct levels of impact from 1975 to 2010, while elsewhere in Europe several cities appear to have caught (or missed) the high-impact 1990s technology wave (Figure 6(e)).





DISCUSSION AND CONCLUSION

Patents and patent citations are among the most widely used and controversial measures in economics, management, public policy, and strategy research. Patent data have played increasingly important roles in empirical research on innovation (Griliches, 1990; Harhoff et al., 1999; Kogan et al., 2017), knowledge flows (Cantwell & Mudambi, 2011; Jaffe et al., 1993), employee mobility (Agarwal et al., 2009), industrial evolution (Stuart & Podolny, 1996), university and public research (Bacchiocchi & Montobbio, 2009; Kolympiris & Klein, 2017), and economic development (Awate et al., 2012). Numerous studies, however, have identified serious limitations in the usefulness and validity of patents and citations as indicators of these phenomena due to noise and bias introduced by measurement error, firm strategy and employee patent policies, patent examiners, the institutional framework of the patent system, and other factors (Alcácer & Gittelman, 2006; Gittelman, 2008; Roach & Cohen, 2012).

As measures of impact based on available patent and citation data, the class- and subclass-level impact values developed in this study are subject to these inherent limitations. Accordingly, these values can and should be used in conjunction with other controls and approaches to address methodological problems and caveats associated with patent data in management research (Gittelman, 2008). Other limitations derive from the methodology used to calculate the impact values. For example, although meticulous processes were designed and followed to properly link individual firms to patents to exclude self-citations from forward citation counts and class impact calculations, assignee names and codes in the patent applications and patent databases vary greatly and change over time. It is likely that some patents for some firms were not correctly captured when calculating the impact values. Additionally, to facilitate the development of this study, patents with multiple assignees were deliberately excluded from the impact calculations. These represented less than 3% of all patents in the USPTO PatentsView data examined. Also, only the first five unique CPC classes sequentially assigned to each patent were retained for analysis; less than 2% of the 6.8 million patents examined had more than five patent classes assigned. More granular studies into specific firms and patent classes using updated patent databases will help to identify weaknesses that can be addressed in this study and its development process.

Despite these limitations, the class-level impact method provides a new approach to patent-based research that can be applied to many areas of interest to innovation and strategic management scholars. In addition to the providing a clearer picture of the evolution of technologies, the methodology used for firm and location comparisons using the class impact values can be applied to examine other units of analysis linked to patents. For example, the levels of innovation quality emerging from university-affiliated incubators (Kolympiris & Klein, 2017) and the efficacy of government grants to regional economic development (Stevenson et al., 2021) can mapped over time, and the changing impact of individual scientists, engineers, and inventors can be traced as their careers evolve (Ge et al., 2016).

This study was designed to provide a new complementary tool for investigating exploration strategies and outcomes. The calculation of a new measure of impact and the uses of it described here can be universally applied and adjusted to suit the needs of studies that examine patents and patenting activity in a variety of research settings and at multiple levels of analysis.

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THE PERVASIVE NATURE OF FRAUD:
A STUDY OF ORGANIZATIONS FROM PRE to POST PANDEMIC

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ABSTRACT

There are a number of reasons fraud proliferates during recessions and times of economic instability. A large factor is the increased pressure companies, and their employees feel as they struggle to meet the challenges of an economic deceleration. For example, struggling companies can face pressure to falsify their financials in order to meet earnings targets or secure financing. The resultant financial statement fraud is also the most expensive type of fraud. There is an immense negative impact from fraud incidents on institutional stability and ultimately repercussions on the economy in general. This paper analyzes ways that the pandemic affected the risk of fraud for firms and auditors, comparing the 2018 and 2022 ACFE (The Association of Certified Fraud Examiners) reports. For example, according to data from the 2019 Global Fraud Survey, financial statement fraud costs an average of $8.7 million. This research further discusses the signs of fraud post- COVID, focusing on occupational fraud. Trends on the risks of fraud are identified and analyzed during this period. Finally, we discuss recommendations in preparing for a post-pandemic fraud landscape.

INTRODUCTION

The COVID-19 pandemic affected many different aspects of American lives, including conceptions about where work is performed. According to the Census Bureau Report (April, 2023), the number of people who worked from home in the U.S. tripled between 2019 and 2021. The amount of people in the workforce increased from 5.7% of the workforce in 2019 to 17.9% in 2021. While this increase in the incidence of working from home is evident across all income groups, it is more prominent amongst the highest-earning group. This group reported the biggest increase in the number of workers working from home jumping from 11% in 2019 to 38% in 2021. Among the industries which evidenced the biggest increases in work from home (WFH) was finance, insurance and real estate, in which 38% of people worked from home compared to only 8% of people in the arts, entertainment, recreation, accommodation and food services industry in 2021. This normalization of the work from home culture has grown ever since, with service professionals seeking a better work-life balance, reducing commute time and improving efficiency and worker productivity.

While employees appreciate the flexibility of work from home arrangements and they were able to reassess their work-life priorities, such changes have an impact on organizations' risks. Whenever organizations plan a major shift in operations, it has to be followed by a proper change in management protocols. With the sudden shift to remote work at the onset of the pandemic, such management planning was harder to implement. As a result, the shift in the work environment has led to higher risk. Although the risks might differ in magnitude by sector and organization, the general threats include data theft, cybercrime and occupational fraud, according to the Association of Certified Fraud Examiners (ACFE), 2023. While data theft and cyber-crimes are examples of external attacks, one of the biggest threats organizations face is from unsupervised employees. The ACFE Report to the Nations provides insights into the factors and toll of occupational fraud. The 2022 ACFE, the largest global study on occupational fraud from 133 countries, reports a median loss of $117,000 in revenue for an average organization due to fraud that equates to a 5% loss, per year.

Given the extent of losses associated with occupational fraud, this research will further analyze the pandemic's effects on the risk of fraud for firms and auditors, comparing the 2018 and 2022 ACFE reports, discuss the signs of fraud post- COVID, and suggest recommendations in preparation for a post-pandemic fraud landscape.

PREVIOUS LITERATURE

With the onset of the pandemic, and the commensurate changes in the workplace, many employees appreciated the flexibility of working from home without having to commute to the office. A study by Barrero, Bloom and Davis (2021) found that a post-pandemic shift to work from home had significant benefits for workers, primarily due to reduced drive times. This flexible work environment also improved worker productivity. In a natural experiment with call center workers at large US firms, Emanuel and Harrington (2021) found that remote work led to an 8% increase in productivity of workers. Another study which conducted a natural experiment involving the U.S. Patent Office workers discovered that a work-from-anywhere approach led to a 4% increase in productivity, Choudhury, Foroughi, and Larson, (2021). Similarly, Angelici and Profeta (2020) report that granting employees some flexibility over when and where to work led to an increase in productivity in a field experiment at a large Italian firm. Work from home has been shown to improve work-life balance for many employees. A study by Tilo (2021) found that employees who work from home are four times more likely to report having an improved work-life balance since the start of the COVID-19 pandemic.

Additionally, Aksoy, Barrero, Bloom, Davis, Dolls, and Zárate, (2022) states “employers plan an average of 0.7 WFH days per week after the pandemic, but workers want 1.7 days.” These results are based on the Global Survey of Working Arrangements (G-SWA) which covers full-time workers, aged 20-59, who finished primary school across 27 countries. This research drew on a near-universe of online job vacancy postings in the United States and four other English-speaking countries, Hansen, Lambert, Bloom, Davis, Sadun, and Taska, (2022) find the number of job postings that offer remote work for one or more days per week, has been increased significantly since mid-2020 through mid-2022. Adrian et al. (2021) found that the share of vacancy positions that offer remote work in 20 OECD countries also increased significantly through September 2021. The growing trend of employers offering remote work options to their employees indicates that this is a practice that was likely here to stay, although recent organizational announcements may indicate a reversal.

While many employees have found that working from home can improve their work-life balance and productivity, some executives are more wary about workers’ productivity at home, and fear that their company culture will take a hit if teams do not work together face-to-face. Barrero, Bloom and Davis (2021) note that “business leaders often mention concerns around workplace culture, motivation, and innovation as important reasons to bring workers back onsite three or more days per week”.

The desire to work remotely has increased tremendously across America. According to Barrero, Bloom and Davis (2021), four in ten Americans who currently work from home at least one day a week would be willing to leave their job if their employer required them to return to the business premises. Workers have become more comfortable with the flexibility and freedom of the hybrid and remote office environments since the pandemic began (Robinson,2022).

Despite the growing popularity of remote work, many large companies including Google, Tesla, Amazon etc., are requiring their employees to come back to their respective office either full-time or part-time. This is a significant trend reversal, as many companies had previously embraced remote work during the COVID -19 pandemic and even touted work from anywhere policies. Remote work is becoming a contentious issue, with both employers and employees taking strong stances on the issue. For example, Tesla CEO Elon Musk has called working from home “morally wrong” and has given his executive staff a choice of either returning to the office or quitting. On the other hand, Amazon workers recently staged a walkout to protest the company’s office policies, which include tracking employees’ in-office attendance and penalizing them for not spending enough time in the office.

However, there are negative impacts of such work from home policies on occupational fraud incidences. The 2021 ACFE survey notes that 51% of organizations have reported more fraud since the onset of the pandemic. A majority (71%) of survey respondents expect the level of fraud impacting their organizations to increase over the next year (Kreston Global, 2021).

OCCUPATIONAL FRAUD

Occupational fraud is usually defined in 3 categories:

- Asset misappropriation – stealing or misuse of company assets – most common, but least costly.
- Corruption – the use of power for personal gain including bribery, extortion or conflicts of interest.
- Financial Statement fraud - intentional misstatement in financial documents – least common, but most costly.

Occupational fraud averages 12 – 18 months before detection. Fraud can be perpetrated by executives at any level, but 3 factors, entitled the fraud triangle are most prevalent: Perceived opportunity – due to a failure in controls or distribution of duties; pressure – often originates from financial challenges; and rationalization – an individual's justification for the fraudulent act. More than 50% of all fraudulent activity occurs in 4 areas; 15% in Operations; 12% in accounting; 11% in Executive / Upper Management; and 11% in Sales.

Red flags in consumer scams may include unusual urgency, the name of the company is similar to other names, the name cannot be found on the internet, cannot take a phone call, an offer to pay in gift cards, a request to send your banking details, etc. (Grimes, 2019). Individual behavioral flags for potential fraud include living beyond one's means, financial difficulties/ history of debts, gambling, unusual close association with a vendor or customer, excessive control issues / unwillingness to share duties, recent divorce or family problems and a general 'wheeler – dealer' attitude toward unscrupulous behavior (Moody, 2018). Internal signs of fraud may manifest in inventory shrinkage, missing documents, an increase in the volume of invoices, multiple payments, excessive entry adjustments, etc. (CFI, 2022).

The number of fraud cases during the period of the COVID – 19 pandemic exploded. According to Ayres and Wilder (2021), the proliferation scanned a myriad of industries from fraudulent exploitation of government stimulus plans to consumer fraud spanning fake cures to counterfeit personal protective equipment (PPEs). Predatory losses from COVID-19, according to Gorman (2020) from Reuters have been reported as $97.5 million by the Federal Trade Commission and include online fraud and unscrupulous callers attempting to defraud fellow Americans.

One of the worst global scandals involved the German financial technology company Wirecard founded in 1999, which processes payments and sells data analytics services. Wirecard, was lauded to be one of Europe's leading fintech firms. Amidst a series of fraud investigations into the firm's accounting practices, by EY, a shortfall of $2 billion was reported missing, resulting in a meteoric decline in its overall worth from $26.9 billion plummeting to $3.6 billion by the end of June 2020 (Riley & McSweeney (2020).

Fraud magazine in 2020 quotes from the Second ACFE COVID-19 report, of the anti-fraud professionals surveyed for the ACFE Fraud in the Wake of COVID-19 Benchmarking Report, September 2020 Edition, listed that 77% have seen an increase in the overall level of fraud as of August, compared to 68% who'd observed an increase when the ACFE published the first COVID-19 report in May. In the ACFE report, The Next Normal: Preparing for a Post Pandemic Fraud Landscape, (2021), 51% of organizations reported that they have uncovered more fraud since the onset of the pandemic.

Ninety-two percent of the survey participants expect the overall level of fraud to continue increasing over the next 12 months. Forty-eight percent expect this increase to be significant. Participants said the top fraud risks, based on current observations and expected increases, are: (1) Cyberfraud (2) Social engineering (3) Identity fraud (4) Unemployment fraud (5) Payment fraud (6) and Fraud by vendors and sellers. Cyberfraud includes business email compromise, ransom and malware, and hacking; and social engineering – phishing and baiting; are the top categories for forecasted growth. Comparing 2019 – 2020, New Yorkers were scammed from a variety of sources from the lottery, sweepstakes, or inheritance scams along with phishing scams, out 50% more money in 2020, for a total of $415,812,917. The FBI listed the state as second in the country for the most money lost, due to fraud, compared to 2019 with $198,765,769 in reported losses (Darmanjian, 2021). This data from the New York State Comptroller's Office, the FTC and the FBI

Cyber Crime Unit, New York alone recorded $1.7 million in healthcare-related fraud, an increase of a staggering 782.62%.

For 2022, 43% expected an increase in their overall anti-fraud budgets and technology over the next year, while 48% expected a similar overall anti-fraud budget. Here are notable changes to specific budget areas:

- 29% expect an increase in budget for travel for anti-fraud staff, while 13% expect a decrease.
- 30% expect an increase in budget for training/professional development for anti-fraud staff. However, 13% expect a decrease in this budget item.
- 54% expect their level of anti-fraud staffing to remain about the same; 29% expect an increase and 11% expect staffing reductions.

A majority - 68% to 76% - say that preventing, detecting and investigating fraud are more difficult now than before COVID-19. This research cites changing consumer behaviors (on-line and virtual retail transactions), and business operations (remote work and work from home) are two of the highest risk elements and primary challenges to anti-fraud programs. These programs are at risk due to changes in investigative processes and in the control / operating environment. Changes in controls and processes due to the migration to remote work, staffing changes and reductions, all add to the obstacles to mitigate fraud. According to more than 60% of the respondents, fraud awareness has increased too due to media coverage of various schemes, heightened efforts by fraud professionals and more internal communication within organizations (ACFE- 2021). In a 2022 Anti-Fraud Technology report through the collaboration of SAS and ACFE, at least 97% of fraud examiners believe that analytics are an essential tool to mitigate fraud through an improvement in timeliness, efficiency and accuracy of the fraud detection programs.

An inability to travel is still the number one challenge in combating fraud. But more people are citing conducting remote interviews as a current top challenge for them, moving this up to the number 2 spot. Examining the trends in financial fraud, Karpoff (2021) in contrast, speculated that the future of financial fraud may have some mixed results. He posits that new and innovative fraudsters along with anonymity may increase the possibility of fraud in the industry. Technological and wealth changes, a decrease in information, search, and transaction expense, may, however, precipitate a decrease in incidents as third-party enforcement and ethical deterrents to fraud increase.

Another area of concern is cryptocurrency, defined by the Federal Trade Commission as "a type of digital currency that generally only exists electronically." It is decentralized digital money designed to be used over the internet and can be invested as tokens or coins. Transactions occur through peer-to-peer networks, while a blockchain maintains the records in a decentralized digital database or ledger. Chaum, (1983) published a paper on eCash, an early version of cryptocurrency, that was developed in the 1990's through the firm, Digicash, that declared bankruptcy in 1998. Bitcoin is considered one of the first forms of cryptocurrency and is now the most popularly traded. First introduced by a programmer under the pseudonym Satoshi Nakamoto, in January 2009, a 2008 whitepaper described the blockchain system as the foundation of the cryptocurrency market. Nakamoto (2008), stated that the peer-to-peer networks use timestamped transactions to create a chain of proof-of-work, thereby forming a blockchain or public record of the transactions. Reviews by investors range from a Ponzi scheme to a trap for unsuspecting investors, to a viable investment vehicle to a speculative craze (Kerr, Loveland, Smith, and Murphy - Smith, 2023 and Nakamoto, 2008). A 2023 study in Risks, (by Kerr, et al) identified a number of high-profile fraud cases involving cryptocurrency. With the potential upside of outperforming the traditional stock market, comes the risk of much higher volatility and the proliferation of fraud cases.

A few of the top fraud cases involving cryptocurrency are (O'Driscoll, 2023):

- 2022 – Ronin network breach - $620 million
- Mt. Gox exchange - $470 million lost, over time but uncovered in 2014
- FTX – Crypto Exchange – November, 2022, hack of about $500 million

Another growing area has been labeled, Cryptojacking, that uses either malware or a browser-based approach to mine cryptocurrency with the computers or devices of others (Lake, 2020). According to the SonicWall Cyber Threat Report

(2022) global crypto jacking has risen to an alarming rate with 12 million attacks and 97 million attempts as of March 2021.

In February, 2023, Bitcoin alone was up 40% year to date, but the industry as a whole is reeling from some of the aforementioned collapses like FTX. The market cap is $1 trillion, so it remains a huge market to be reckoned with, according to market experts like Marion Laboure from Deutsche Research. Still other critics believe that it is simply the next Dutch Tulip Bubble (a boom-and-bust craze), whereby investors will be left with nothing as the asset bubble crashes when the asset price is not reflected in the value.

In 2022, the FBI in its Internet Crime Report estimated that on-line fraud including tech support, extortion, non-payment / non-delivery, personal data breach and phishing totaled $10billion. The chart below depicts the proliferation of worldwide internet scams.

Cryptocurrency can generally be used for e-commerce, often using digital wallets. Merchants may choose to accept cryptocurrency either directly or indirectly through a service provider. Companies such as Microsoft, PayPal, Starbucks, Overstock and AT&T have adopted cryptocurrency as a payment option.

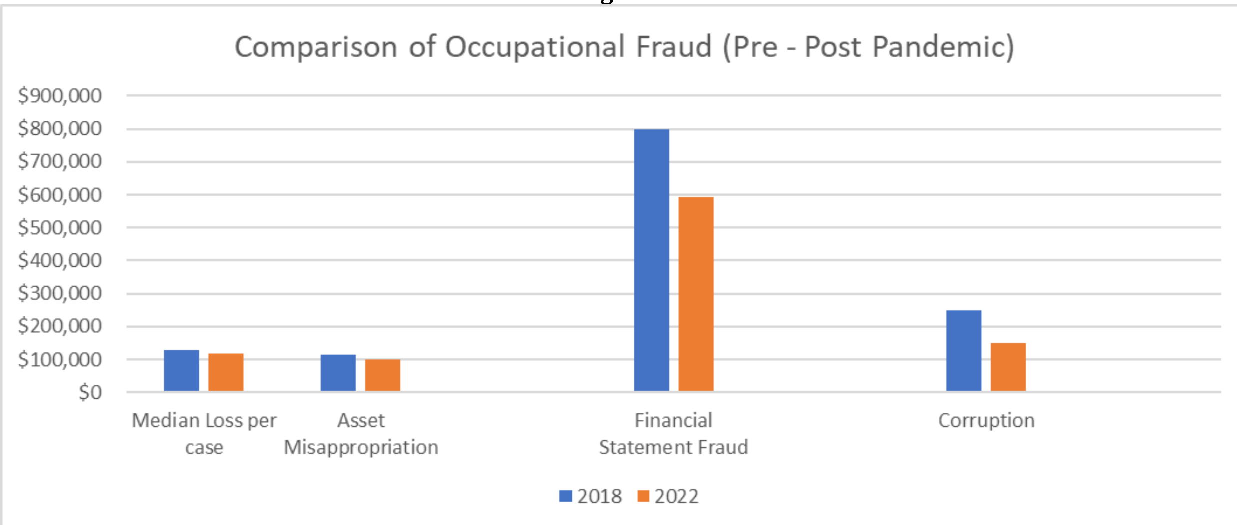
COMPARISON OF PRE AND POST PANDEMIC FRAUD

The rapid shift to digital operations during the pandemic made many organizations susceptible to fraud. However, the comparison of 2018 and 2022 ACFE Report to Nations shows a downturn in fraud as reported in Table 1 below.

Table 1
Comparison of 2022 and 2018 ACFE Report Findings

	2022	**2018**
Number of Cases	2110 cases	2690 cases
Total Losses of more than	$3.6 billion	$7 billion
Median Loss per case	$117,000	$130,000
Asset Misappropriation (Median Loss)	$100,000	$114,000
Financial Statement Fraud (Median Loss)	$593,000	$800,000
Corruption (Median Loss)	$150,000	$250,000
Median Duration of Fraud	12 months	16 months

Figure 1



The Figure 1 above indicate a decline in overall fraud cases as well as in the losses reported from occupational fraud between 2018 and 2022. However, it should be noted that while the changing business landscape during the pandemic increased the fraud risk for organizations, detecting and investigating fraud have become increasingly more difficult. Instances such as someone living beyond their means, which are common red flags of fraud are harder to detect during remote work on a video call. During the pandemic, many organizations reported receiving fewer tips from employees since remote work made it harder for employees to spot red flags and report them. Hence significant levels of occupational fraud were undetected or unreported during this time (ACFE 2021).

FRAUD SIGNS AND TRENDS POST PANDEMIC

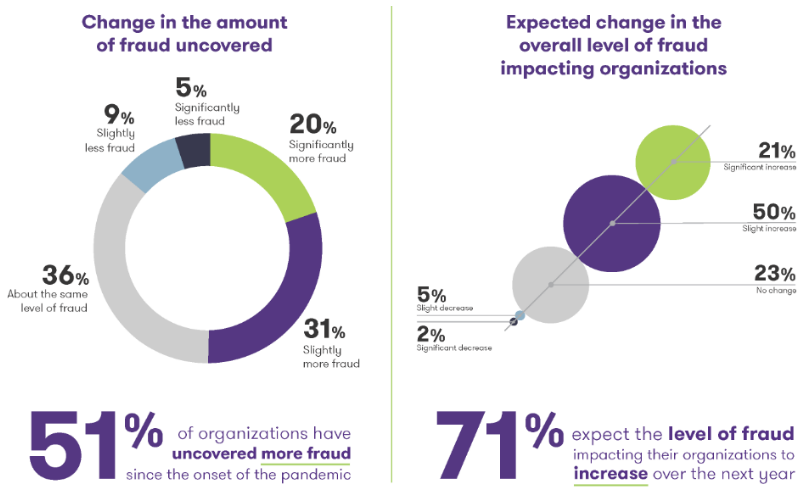
In order to acknowledge the effects of the pandemic, many organizations had to alter their work environments, which included allocation of resources, staffing and operations. Combined together, these changes prompted incentives for employees to commit fraud.

The Figure 2 below summarizes the ACFE (2021) findings regarding the percentage of organizations which uncovered additional fraud since the onset of the pandemic. A vast majority of survey respondents fear that the level of fraud in their organization will increase over the following year.

The ACFE survey identified certain roadblocks in the prevention and detection of fraud during the pandemic. These included issues such as changes to investigative processes and operating environments, as well as uncertainty about how the pandemic has changed the risk of fraud.

We can examine the increased risk of fraud due to change in work environment through the lens of the Fraud Triangle, which states that "individuals are motivated to commit fraud when three elements come together: 1) some kind of perceived pressure 2) some perceived opportunity 3) some way to rationalize the fraud as not being inconsistent with one's values."

Figure 2



Source: The ACFE and Grant Thornton's Report, The Next Normal: Preparing for a Post-Pandemic Fraud Landscape

RECOMMENDATIONS FOR POST PANDEMIC FRAUD LANDSCAPE

A significant shift in business operations and changes in consumer behavior during the COVID-19 pandemic had a profound impact on fraud risk. With the ACFE report (2021) findings indicating over 71% of organizations expecting fraud incidences to increase, business leaders need to address this issue and incorporate measures into their risk assessments and anti-fraud plans. Organizations need to strengthen their anti-fraud resources in response to the likely increase in fraud.

Measures to detect and prevent fraud incidents include:

- *Budget:* budgetary and staffing support available to anti-fraud programs can have a significant impact on the effectiveness of detection and prevention of fraud. ACFE (2021) report notes that 38% of organizations surveyed increased their budgets for anti-fraud technology, and have confirmed a commitment of continued investment in such anti-fraud programs.
- *Adjustments to existing anti-fraud programs:* a vast majority of organizations have implemented changes to their anti-fraud programs in response to the risks and circumstances of the pandemic. In particular, conducting internal fraud awareness training and updating a fraud risk assessment are the most common initiatives undertaken by the organizations. Other actions include making operational changes to the risk management program, creating a fraud risk map and conducting external fraud awareness training.
- *Invest in Anti-Fraud Programs:* investing in anti-fraud activities such as establishing a Code of Conduct for your organization to reduce losses and limit the duration of fraud, obtaining fraud insurance, and implementing an internal audit function in the organization. If smaller organizations find this cost-prohibitive, it could be considered as an outsourced activity to better fit the needs of organizations of varying sizes.
- *Fraudulent Emails and Texts:* using the phone to ensure whether a correspondence is legitimate instead of responding via email, as there are higher chances of email being hacked. Being aware of unsolicited communications, especially from governmental agencies such as the IRS or SBA. These organizations do not contact businesses unsolicited via phone or email.
- *Empower employees:* many fraudulent disbursements occur because employees do not want to bother their manager for fear of appearing incompetent. It is important to make employees a part of the team to help fight fraud in the organization. Encouraging employee participation in fraud prevention with praise and reward will set a tone of proactive transparency (Campbell. 2022)

CONCLUSION

The COVID-19 pandemic brought about significant changes in the workplace, with a rapid shift to remote work and digital operations. While many employees enjoyed the flexibility of working from home, this transition also introduced new challenges and risks for organizations, particularly in terms of fraud. This paper analyzed the impact of the pandemic on fraud risk for firms and auditors, comparing data from the 2018 and 2022 reports by the Association of Certified Fraud Examiners (ACFE).

The ACFE reports revealed a decline in both the number of fraud cases and the total losses reported between 2018 and 2022. However, this reduction in reported fraud cases should not be misconstrued as a decrease in fraud risk. Detecting and investigating fraud became more challenging during the pandemic due to remote work, which made it harder for employees to spot red flags and report incidents. Many instances of occupational fraud likely went undetected or unreported during this time.

Occupational fraud can manifest in various forms, including asset misappropriation, corruption, and financial statement fraud. It typically takes 12 to 18 months before detection, and it often involves individuals who see an opportunity, feel financial pressure, and can rationalize their actions. Red flags for potential fraud include living beyond one's means, financial difficulties, close associations with vendors, and more.

The paper has also highlighted the increasing risk associated with cryptocurrency, as its usage and investment have grown significantly. The crypto market has seen both tremendous growth and a surge in fraudulent activities, including high-profile cases of breaches and scams.

In response to the evolving fraud landscape, organizations need to take proactive steps to mitigate fraud risk, which are discussed in the paper. As organizations continue to adapt to the post-pandemic work environment, addressing fraud risk is essential for maintaining stability and financial security. While the numbers of reported fraud cases may have decreased, the changing landscape of remote work and evolving tactics by fraudsters require continued vigilance and proactive measures to protect against occupational fraud and related risks.

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